The Demand for, and Avoidance of, Information

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Abstract

We apply a previously developed "information gap" framework (Golman and Loewenstein, 2018) to better understand and predict information seeking and avoidance. The resulting theory posits that, beyond the conventional desire for information as an input to decision making, two additional motives contribute to the demand for information: *curiosity*—the desire to fill information gaps, i.e., to answer specific questions that capture attention; and *motivated attention*—the desire to savor good news and ignore bad news, i.e. to obtain information we like thinking about and avoid information we do not like thinking about. Five experiments ($N = 2,361$) test three of the primary hypotheses derived from the theory about the demand for information both when information is neutrally-valenced and when it is ego-relevant. People are more inclined to acquire information: a) when it seems more *important*, even when the information is not instrumental for decision making (Experiments 1A & 2A); b) when it is more *salient*, manipulated by how recently the information gap was opened (Experiments 1B & 2B); and c) when it has higher *valence*—i.e., when individuals anticipate receiving more favorable news (Experiment 2C). This set of findings demonstrates that we gain insight into informational preferences by recognizing how information gaps attract attention.

KEYWORDS: curiosity, information gap, motivated attention, ostrich effect

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1 Introduction

Good decision making depends on the information people have, but they may be wary of information that challenges their existing beliefs, warns of impending bad outcomes, or addresses problems not currently on their radar. People may be more inclined to look at information that feels reassuring or that simply grabs their attention. When managers or policy makers want to disseminate information to other decision makers (e.g., customers, strategic partners, shareholders, etc.), they need to cut through the cacophony of competing information campaigns, and in some cases overcome avoidance of potentially unpleasant information, to get people to listen. In these situations and many others, it would be helpful to know when and why people either seek out information or avoid it. We develop a theory offering comprehensive predictions about when, and how strongly, people will want to acquire or avoid information, and we provide evidence from five experiments supporting three of our theory's predictions.

The standard economic theory of information (Stigler, 1961) assumes that people seek out information because, and only to the extent that, it enables them to make superior decisions. Such an account predicts that (outside of strategic situations) valid information will never be valued negatively since, at worst, it can be ignored, i.e., not taken into account in decision making. Yet there are many situations in which people actively *resist* acquiring information (Hertwig and Engel, 2016; Golman et al., 2017). For example, people often choose to not obtain medical tests, even when the test is costless (e.g., simply checking a box when giving a blood sample) and would provide valuable information for decision making (e.g., whether to obtain treatment). At the same time, people also seek out information, such as celebrity gossip, that does not benefit decision making (Kruger and Evans, 2009; Eliaz and Schotter, 2010; Hsee and Ruan, 2016).

Our theory of information seeking and avoidance is unique in highlighting the role of attention. It assumes that people derive utility from their beliefs, weighted by the attention devoted to them, and that information not only informs decision making but also directly impacts utility by changing beliefs and redirecting the focus of attention (Golman and Loewenstein, 2018). Golman and Loewenstein (2018) presents the model of utility from thinking about beliefs, but leaves for future work the critical task of deriving and testing the model's predictions for information seeking and avoidance. Here we use that model to generate testable predictions about contextual factors that stimulate demand for information. The theory reconciles disconnected sets of empirical findings across different domains and makes new predictions that we test, and find support for, in this paper. While other theories recognize that people sometimes seek useless information or avoid useful information, our theory is unique in predicting that contextual factors affecting attention determine when these non-standard informational preferences occur.

The theory incorporates two important motives underlying the desire to obtain or avoid information, on top of the traditional instrumental value of information. First, individuals may seek or avoid information because they anticipate that what they discover will be pleasurable or painful (as in Caplin and Leahy, 2001; Kőszegi, 2010). Beliefs can be pleasurable or painful for many reasons—for instance, they can evoke anticipatory emotions or affect one's self-concept. From a Bayesian perspective, it might seem strange that a decision maker would expect that obtaining information, which by its very nature is not known, would have a non-zero expected impact on belief-based utility (see Eliaz and Spiegler, 2006). However, we assume that obtaining news tends to increase attention to it (as in Gabaix et al., 2006); i.e., to know something, at least at the moment of finding out, has a greater impact on utility than to merely suspect it (see Karlsson et al., 2009). This impact-magnifying effect of new information leads people to seek information about questions they like thinking about and avoid information about questions they do not like thinking about. Second, people may seek information to satisfy curiosity (see Gottlieb et al., 2013; Kidd and Hayden, 2015; Buyalskaya and Camerer, 2020). There are countless things people want to know despite having no practical use for the information. People incur real costs to indulge their curiosity (Kruger and Evans, 2009; Eliaz and Schotter, 2010; Hsee and Ruan, 2016; Alos-Ferrer et al., 2018). We conceive of curiosity as a fundamental desire to fill 'information gaps'—specific unanswered questions that capture attention (Loewenstein, 1994). Curiosity may inspire people to acquire non-instrumental information, while the motive to direct attention to more favorable beliefs may inspire people to avoid potentially useful information.[1]

To illustrate the trade-offs involved in information acquisition or avoidance, consider a person deciding whether to obtain some performance feedback, for example, an employee deciding whether to read her manager's evaluation of her. Getting the feedback would inform a decision about how to improve in the future, so the information has instrumental value. The information would impact hedonic utility as well. If the employee learns that her manager is satisfied with her performance, and pays more attention to this belief, she will feel good; if she learns of a poor evaluation and dwells on it, she will feel bad. A desire to focus attention on, or away from, this ego-relevant belief promotes looking if she anticipates good news and not looking if she anticipates bad news. Yet, if she remains uncertain and cannot forget about it, nagging curiosity may push her to find out.

We derive testable predictions about when people will be more motivated to seek or avoid information, accounting for a range of empirical findings which had not yet been fit together within a coherent, comprehensive model. We also obtain novel predictions about how attention affects demand for information: We predict that making a question more important stimulates curiosity for finding out the answer because higher importance (defined as greater potential impact on utility, not necessarily corresponding to greater instrumental usefulness) directs more attention to the presence of an information gap. Similarly, we predict that making a question more salient (defined as directing attention to it through contextual factors) also stimulates curiosity for the answer. People may seek this information even for epistemic questions for which they have no strict preferences between the possible answers. Additionally, when beliefs have valence, the motive to direct attention away from questions one does not like thinking about, and toward questions one likes thinking about, leads to stronger desire for information when the anticipated answers have higher valence.

We test these predictions in five online experiments ($N = 2,361$) that focus on the demand for non-instrumental information. We conduct these experiments in two domains: 1) offering neutrally-valenced, epistemic information (i.e., individuals can find out the answer to a riddle), to capture the effect of attention on curiosity *absent* any desire to redirect attention away from bad news; and 2) offering ego-relevant information, which could be construed as good or bad news (i.e., individuals can learn about their performance on a test). In both domains we show that, absent any instrumental value, amplifying attention by manipulating the perceived importance of a given question (an answer to a riddle in Experiment 1A or one's performance

[1]These motives fit into Sharot and Sunstein's (2020) framework as well. Motivated attention to favorable beliefs (and away from unfavorable beliefs) has "hedonic value," and curiosity has "cognitive value."

on a test in Experiment 2A) stimulates the desire to fill the information gap (i.e., to find out the answer to the riddle, or to reveal the results of the test). In both domains, we also show that demand for information is higher when the information gap had been opened more recently, i.e., when it is more salient (Experiments 1B and 2B). Finally, in the ego-relevant domain, where the motive to redirect attention away from bad news is at play, we manipulate the valence of feedback the participants could receive about their performance on a test and confirm the model's prediction that demand for non-instrumental information is higher when individuals expect to receive good news (i.e., when the anticipated answers have higher valence). This set of findings cannot be explained by other theories of information acquisition or avoidance.

Our theory offers many new insights, capturing the role of contextual factors that are overlooked in existing work, and bringing together demand for non-instrumental information and avoidance of potentially useful information, which have been modeled separately before. Previous treatments of the demand for non-instrumental information have posited that people have intrinsic preferences regarding the resolution of uncertainty (Grant et al., 1998; Cabrales et al., 2013; Ely et al., 2015) or intrinsic preferences for information that may give them confidence in decisions they are about to make (Asch et al., 1990; Eliaz and Schotter, 2010). The predictions of these models do not distinguish different sources of uncertainty with identical probabilistic structure. For example, if two football games went into overtime with identical probabilities of one's preferred team winning and identical probabilities of all interim events, these models would predict the same level of curiosity to see each game play out, even if one game was shown live and the other on tape delay or even if the viewer had just tuned into one game but had attentively watched the other game from the beginning. By contrast, we distinguish between different information gaps according to the attention devoted to each, so that a person may be very curious to fill one gap while indifferent to another with similar probabilistic structure. We thus predict that curiosity will vary with situational determinants (see Loewenstein, 1994), since a variety of contextual factors can affect attention to information gaps and, thus, demand for information. Our experiments provide supportive evidence that amplifying attention by increasing the importance or the salience of an information gap strengthens the preference for filling it.

Previous treatments of information avoidance have generally derived it (a) from non-standard risk preferences (e.g., Kreps and Porteus, 1978; Wakker, 1988; Grant et al., 1998; Dillenberger, 2010; Andries and Haddad, 2020), (b) from belief-based utility with risk aversion or loss aversion (e.g., Caplin and Leahy, 2001; Kőszegi, 2006; Karlsson et al., 2009; Kőszegi, 2010; Pagel, 2018), i.e., from assuming that negative surprises have more impact than positive surprises, or (c) from optimism, i.e., from assuming that people can choose favorable beliefs in the absence of information (e.g., Brunnermeier and Parker, 2005; Oster et al., 2013). A limitation of many of these models is that they make the unrealistic prediction that a person who avoids information when anticipating bad outcomes must also avoid information when anticipating good outcomes, as highlighted by Eliaz and Spiegler (2006). Our theory is not subject to this critique because it accounts for information avoidance as a result of the desire to avoid increasing attention to unpleasant beliefs. Thus, avoiding information when anticipating bad outcomes is consistent with demanding information when anticipating good outcomes, in line with the results of our third experiment as well as previous empirical findings (Karlsson et al., 2009; Eil and Rao, 2011; Ganguly and Tasoff, 2016; Gigerenzer and Garcia-Retamero, 2017). Furthermore, models based on anticipatory utility or on optimism also predict no preference for information when people do not care at all about the outcomes (e.g., for epistemic information, such as finding out the answer to a riddle). By contrast, our theory not only accounts for the finding that information avoidance is more common when beliefs are more negatively valenced, but also predicts that people experience curiosity for the answer to a question even when all answers have neutral valence, simply to fill an information gap.

The remainder of the paper is organized as follows. Section 2 reviews the information-gap model introduced by Golman and Loewenstein (2018), developing its application to preferences for information more fully than in that paper, and offers testable predictions about the demand for information. Section 3 presents experiments testing these predictions, demonstrating that different factors that govern attention to an information gap or that influence the valence of the information gap affect demand for non-instrumental information that fills that gap. Section 4 discusses additional predictions of the theory, including other drivers of curiosity and implications for information avoidance and individual welfare. Section 5 concludes.

2 Theory

2.1 Attention-Based Utility

Our theory incorporates a form of belief-based utility in which attention to beliefs modulates their impact on utility. We represent attention to different beliefs using Golman and Loewenstein's (2018) question-and-answer framework, presented in Appendix A. In this framework, we define an information gap as a question that one is aware of but for which one is uncertain between possible answers. We thus distinguish the specific uncertainties that a person is paying attention to from the many other things the person does not know and does not think about. Utility depends on beliefs and the attention paid to them, but not on uncertainties that do not capture attention. We denote the utility function as $u(\pi, \mathbf{w})$, where π is a probability measure representing beliefs and $\mathbf{w}$ is a vector representing attention to each question (i.e., each belief). To make precise predictions, we use the specific utility function proposed by Golman and Loewenstein (2018) and presented in Appendix A. It assumes that beliefs contribute to utility to the extent a person pays attention to them, allows certain beliefs to have intrinsic value or valence, and captures a general aversion towards uncertainty, the latter of which is also evident from typical patterns of neural activity (see, e.g., Hirsh and Inzlicht, 2008; Gottlieb et al., 2014). We do not treat beliefs (or attention) as choice variables—something that an individual could freely choose—but focus on decisions of whether or not to acquire information to influence beliefs (and attention).

2.2 Attention

Golman and Loewenstein (2018) propose that three factors—importance, salience, and surprise—contribute to the attention weights. A question is important to the extent that one's utility depends on the answer. Notably, questions can be important without having instrumental value, as a person may care about the answer even if it does not affect decision making. We characterize the *importance* of a question as a function of the distribution of utilities that would result from different answers to the question. If this distribution becomes more (or less) spread out, the question becomes more (or less) important. For instance, an opportunity to gain or lose a large amount of money (or self-esteem, or hope) depending on the answer to a question can make that question more important, even if knowing the answer has no instrumental value (as in Experiments 1A and 2A in Section 3). If an answer is known with certainty, then by our definition there is no spread in possible utilities, so the underlying question is no longer important. However, we assume that acquiring information, and revising beliefs, does not affect the importance of the questions being addressed until the person adapts to the new beliefs.

Salience reflects the degree to which a particular context highlights a question, possibly due to the passage of time (as in Experiments 1B and 2B in Section 3), the presence of distractions, comparison and contrast, or social cues. For example, awareness that performance feedback has been provided to a peer would make questions about one's own performance on the same task more salient. These questions would be more salient immediately after completing the task than they would be days later. And working on an engaging, unrelated task would make these questions less salient.

The *surprise* one experiences upon acquiring new information reflects the degree to which this information changes existing beliefs. We assume that the degree of surprise associated with a revised belief about a question when some information is obtained is the Kullback-Leibler divergence of the revised belief about that question against the prior belief about that question. Surprise is positive with any new information and is greatest when one learns the most unexpected answer with certainty. However, the feeling of surprise is not permanent. We assume that when the decision maker adapts to new information it ceases to be surprising.

2.3 Preferences about Information

A choice to acquire information is essentially a choice to accept a lottery over beliefs (and attention) because, ex ante, one cannot know what one will discover. In the absence of information, an individual has beliefs π^0 and attention $\mathbf{w}^0$. Upon learning answer A_i to question Q_i, beliefs change from π^0 to $\pi^{A_i} = \pi^0(\cdot|A_i)$ due to conditioning of beliefs on the discovered answer, and attention changes from $\mathbf{w}^0$ to $\mathbf{w}^{A_i}$ due to surprise. We assume *Bayesian updating*, as well as an *expected utility* representation for the utility of a lottery over beliefs and attention.[2] Assuming that backward induction is used to evaluate a sequence of actions, where early actions may reveal information that will inform later actions, we define a utility function contingent on the set $\mathcal{S}$ of sequences of actions that may subsequently be chosen:

$$U(\pi, \mathbf{w} \,|\, \mathcal{S}) = \max_{s \in \mathcal{S}} u\left(s \cdot (\pi, \mathbf{w})\right).^3 \tag{1}$$

It follows directly that the utility of receiving information can be captured as the difference between the expected utility after receiving the information and the ex ante utility before receiving the information. The desire for information answering question Q_i, given prior belief π^0 and attention $\mathbf{w}^0$ and with a set $\mathcal{S}$ of subsequent sequences of actions available, is:

$$D_i \;=\; \left(\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i)\, U\big(\pi^{A_i}, \mathbf{w}^{A_i} \,|\, \mathcal{S}\big) \right) \;-\; U\big(\pi^0, \mathbf{w}^0 \,|\, \mathcal{S}\big)\,. \tag{2}$$

[2] Nonlinear probability weighting or reference-dependent valuation are as plausible for information preferences as for those involving only outcomes, but would add extra complexity.

[3] We represent a sequence of contingent actions $s \in \mathcal{S}$ as a single operator with the convention that each action operator passes through a distribution over cognitive states, akin to reduction of compound lotteries over cognitive states.

Naturally, when D_i is positive (or negative), an individual seeks (or avoids) the answer to question Q_i. Learning the answer to a question has three consequences:

1. The information may affect the value of subsequent actions that may be chosen from $\mathcal{S}$.
2. The information may change the probabilities associated with different answers ($\pi^0 \longrightarrow \pi^{A_i}$).
3. The information may change the attention weights ($\mathbf{w}^0 \longrightarrow \mathbf{w}^{A_i}$).

We can now identify in Equation 2 three corresponding sources for the desire to acquire or to avoid information: 1) the instrumental value of that information; 2) curiosity; and 3) motivated attention.

Instrumental value is the difference between the expected utility gain from subsequent actions after having acquired the information and the utility gain that could be derived from subsequent actions without having this information (Hirshleifer and Riley, 1979). The instrumental value of information answering question Q_i, when the set $\mathcal{S}$ of subsequent sequences of actions is available, is

$$D_i^{\mathrm{IV}} = \left(\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) \max_{s \in \mathcal{S}} D(s \,|\, \pi^{A_i}, \mathbf{w}^{A_i}) \right) \; - \; \max_{s \in \mathcal{S}} D(s \,|\, \pi^0, \mathbf{w}^0), \tag{3}$$

where $D(s \,|\, \pi, \mathbf{w}) = u\left(s \cdot (\pi, \mathbf{w})\right) - u\left(\pi, \mathbf{w}\right)$ is the desirability of a sequence of actions s relative to doing nothing. In our framework, information can have instrumental value either if it supports a better choice among subsequent actions or if it makes an intended subsequent action more (or less) attractive.[4] As an example of this latter form of instrumental value, a person reading a novel might ask a friend not to give away the ending, temporarily avoiding information until it will have the most impact (and thus not ruining a good surprise). Similarly, a dieter might refuse to read nutritional facts about a dessert he has already decided to eat so he can enjoy it unencumbered by thoughts of its health consequences, or to avoid subsequent guilt (Woolley and Risen, 2018). While instrumental value derived from the usefulness of information is positive whenever dynamic consistency holds, it may be negative if dynamic consistency is violated, possibly due to moral wiggle room (Dana et al., 2007), temptation (Woolley and Risen, 2018), motivation maintenance (Bénabou and Tirole, 2002), or the curse of knowledge (Camerer et al., 1989). Additionally, instrumental value derived from complementarity or substitutability with subsequent actions can be positive or negative.

Curiosity is an intrinsic desire for knowledge that occurs when an individual becomes aware of a gap in his or her knowledge that could potentially be filled by information (Loewenstein, 1994). In our framework, an information gap opens when a specific unanswered question Q_i captures attention. We identify curiosity for the answer to question Q_i as

$$D_i^{\mathrm{C}} = \left(\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) \, u\left(\pi^{A_i}, \mathbf{w}^0\right) \right) \; - \; u\left(\pi^0, \mathbf{w}^0\right). \tag{4}$$

This is the gain in utility from updating beliefs, holding attention fixed. In general, D_i^{C} could be positive or negative, but if we apply Golman and Loewenstein's (2018) utility function with a cost of uncertainty (in the

[4]We admit that people do not typically accurately assess the usefulness of information (see, e.g., Hoffman, 2016). For simplicity, we assume that people know their own utilities, but this assumption could be modified to allow for heuristic assessment of instrumental value.

form of entropy times attention weight), then $D_i^{\mathrm{C}} \geq 0$, because ex-post beliefs cannot be expected to be any better or worse than ex-ante beliefs, and acquiring information decreases expected entropy (see, e.g., Cover and Thomas, 1991, p. 27). This aligns with our conception of curiosity as a motive for information-seeking.

Consistent with the view that curiosity supports sense-making (Chater and Loewenstein, 2015) rather than simple uncertainty reduction (Cabrales et al., 2013), our theory predicts that curiosity arises only for information that addresses one or more questions that a person is already asking (see Berlyne, 1954). The association of curiosity with an information gap that is attracting attention suggests a natural explanation for the fact that, as Kang et al. (2009) reported, subjects are better able to recall the answers to questions that they have previously reported being curious about. To wit, curiosity results, in part, from increased attention on a question, which should aid memory for the answer. Indeed, Kang et al. (2009) link curiosity to pupil dilation, a well-known, reliable measure of attention (Kahneman, 1973).

Motivated attention to (or avoidance of) information arises from the impact of obtaining information on attention. We express this as

$$D_i^{\mathrm{MA}} = \sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) \, \left(u\left(\pi^{A_i}, \mathbf{w}^{A_i}\right) - u\left(\pi^{A_i}, \mathbf{w}^0\right) \right). \tag{5}$$

Motivated attention may either contribute to the desire to seek information or drive avoidance of information, depending on the valence of anticipated beliefs. According to our theory, revising a belief attracts attention through surprise. Naturally, people prefer to think about positive rather than negative situations, so they tend to desire information about questions with positively valenced answers and to avoid information about questions with negatively valenced answers. For example, most people enjoy opening a gift (in addition to receiving it) because they experience a pleasant surprise. On the other hand, most people do not enjoy going to see the doctor for a diagnosis.

Putting together these three motives yields the desirability of information answering question Q_i:

Theorem 1

$$D_i = D_i^{IV} + D_i^{C} + D_i^{MA}. \tag{6}$$

Theorem 1 states that three motives contribute to the desire for information: instrumental value, curiosity, and motivated attention.

2.4 Predictions about the Demand for Information

According to our theory, directing attention to (or away from) the presence of an information gap can increase (or decrease) demand for information due to the curiosity motive, and shifting the valence of potential beliefs can affect demand for information due to the motive to direct attention away from bad news (and toward good news). This leads to a wide range of testable predictions. We present our primary hypotheses here and discuss additional predictions in our discussion section.[5]

[5]Proposition 1 in Appendix A formally derives these predictions. The validity of hypotheses H1 and H2 in the domain of negative beliefs relies on an ancillary assumption that the effect of surprise on attention is independent of the prior level of attention;

H1 Increasing the *importance* of a question increases demand for information pertaining to that question.

H2 Increasing the *salience* of a question increases demand for information pertaining to that question.

H3 Uniformly increasing the *valence* of the answers to a question increases demand for information pertaining to that question.

Hypothesis H1 holds because curiosity tends to be stronger about questions that an individual considers as more *important*. Although information with higher instrumental value is typically seen as more important, recall that, by our definition, having instrumental value is not a necessary condition for importance. People may perceive information as important even when it cannot affect their future decisions, simply because it does affect their utility. As people tend to care about material outcomes even when those outcomes are beyond their control, hypothesis H1 suggests that people will be more curious when the stakes are higher.

Hypothesis H2 holds because curiosity tends to be an increasing function of the *salience* of the information gap. For example, consider an employee's desire to know the results of her annual performance evaluation. If the evaluation was conducted a long time ago, it is no longer very salient, and she may have already forgotten about it. But, if the evaluation took place recently (and especially if the employee's supervisor already knows the results and has scheduled a meeting to discuss them), it would be much more salient. We would thus predict that the employee would be more curious about her performance feedback in the latter scenarios. Note that while we generally believe that time delay decreases salience, the length of the delay may be relevant. In conversation or advertising, salience may be heightened by a well-timed "pregnant" pause. Indeed, people report greater curiosity after such pauses (Kupor and Tormala, 2015).

Hypothesis H3 holds because motivated attention generates stronger desire for information as the valence of anticipated beliefs increases. Returning to the example of the performance feedback, if the employee is uncertain whether she got the *best* evaluation among her colleagues or "merely" an excellent rating (i.e., all possible answers have positive valence), then she would enjoy looking at (and thinking about) her performance report. On the other hand, if she is uncertain whether she failed to meet expectations along a single criterion or disappointed her supervisor in multiple ways (i.e., all possible answers have negative valence), then looking at (and thinking about) her report is likely to be unpleasant. The employee of the month is likely to eagerly review her report (over and over again), whereas the struggling worker is more likely to quickly dispose of it without a glance or hide it in a place where it will hopefully be forgotten. Hypothesis H3 makes sense of a variety of existing empirical findings. For example, willingness to pay for an assessment of one's IQ or beauty (relative to others) increases as one's subjective prior belief about this assessment becomes more favorable (Eil and Rao, 2011; Möbius et al., 2011; Burks et al., 2013). The well-documented 'ostrich effect' is the finding that investors tend to look up the value of their portfolio—figuratively to "shake their piggy-bank"—when markets are up, but not when they are down (Karlsson et al., 2009; Sicherman et al., 2015). Similarly, people are more likely to look up the value of their bank accounts immediately after getting paid (Olafsson and Pagel, 2017).

these predictions about decreased information avoidance could fail if prior attention amplifies surprise, but they would still hold as predictions about demand for information in the domain of neutral or positive beliefs.

3 Experimental Evidence

We report data from five online experiments aimed at testing the three predictions presented in Section 2 (see Table 1). In Section 3.1, we present data from two experiments that study demand for epistemic information using a paradigm in which anticipated beliefs have neutral valence, and therefore there is no desire to avoid information. These experiments show that individuals are willing to exert effort to acquire non-instrumental information (the answer to a rebus puzzle). In this domain, we test hypotheses H1 and H2 and find that increasing the importance or the salience of an unanswered question increases demand for finding out the answer. In Section 3.2, we again test these hypotheses using ego-relevant information (score on a test), whereby individuals could hold negative beliefs that could motivate information avoidance. On top of testing H1 and H2, this paradigm also lets us test hypothesis H3—that manipulating the valence of anticipated beliefs affects demand for information.

Table 1. The Experiments

Experiment	**Information (Valence)**	**Paradigm**	**Hypothesis**	**Treatments**	**Sample Size**
1A	Epistemic (Neutral)	Rebus Puzzle	H1: Importance	*High Importance* *Low Importance*	$N = 838$
1B	Epistemic (Neutral)	Rebus Puzzle	H2: Salience	*Immediate* *Delayed*	$N = 157$
2A	Ego-Relevant (Valenced)	FER Test	H1: Importance	*High Bonus* *Low Bonus*	$N = 470$
2B	Ego-Relevant (Valenced)	FER Test	H2: Salience	*Immediate* *Delayed*	$N = 398$
2C	Ego-Relevant (Valenced)	FER Test	H3: Valence	*Easy* *Hard*	$N = 498$

In all experiments, we capture demand for information by measuring individuals' willingness to spend time and exert effort to obtain information. We conducted all of our experiments on an online labor market platform, Amazon Mechanical Turk, where workers can browse different tasks and choose which ones to complete in exchange for monetary compensation. In this setting, the choice of spending extra time and exerting effort merely to obtain information (without being compensated for the extra effort) is consequential, as it generates a clear opportunity cost: workers can choose to spend this extra time on other available tasks and can get compensated for it. We choose this outcome measure rather than eliciting participants' willingness to pay for information because requiring an expenditure of time and effort to obtain information creates a decision that is more naturalistic and similar to decisions encountered commonly in everyday life.

3.1 Epistemic (Neutrally-Valenced) Information: The Rebus Puzzle Paradigm

We first report data from two experiments that investigate demand for information while keeping the valence of this information neutral, thereby eliminating the motive to direct attention away from bad news and allowing us to isolate the curiosity motive. We study how the importance and salience of an information gap affect the demand for information in this domain.

We designed a novel experimental paradigm in which participants could exert effort to learn the answer to a challenging rebus puzzle. In the experiments, participants first try solving two practice puzzles and then can earn a $2 bonus payment by successfully solving three bonus puzzles. The final puzzle is quite challenging (only 37% of participants could solve it in a pre-test), so the majority of participants fail to solve it (and thus fail to obtain the bonus). After completing the task, participants have the opportunity to exert effort to reveal the answer to the last puzzle. We ask participants if they are interested in learning the solution to this puzzle ('YES' or 'NO'). Participants who click the 'YES' button then get a pop-up message that instructs them to click the button again if they want to see the solution. They have to click 'YES' a number of times (ten times in Experiment 1A; five times in Experiment 1B) to actually see the solution, but they do not know this number ahead of time. During each iteration, participants can choose to click 'YES' to indicate they want to see the solution or 'NO' to skip revealing the solution and conclude the survey immediately. Note that in each iteration we simply instruct participants to click again if they want to see the solution, without promising them that the solution would be immediately displayed. If participants revise their expectation about the necessary number of clicks upwards every time they are asked to click another time, they may experience an increasing cost associated with revealing the solution. Since participants did not know whether the repeated pop-up message was an error or a feature of the experiment, it is possible that they became increasingly frustrated after repeatedly failing to reveal the solution. We treat frustration as a potential type of cost associated with revealing the solution (in addition to effort and time), and our predictions are robust whether participants became increasingly frustrated or not. We expect participants to stop clicking when the cost exceeds the expected gain in utility from satisfying curiosity. We estimate curiosity about the solution by measuring the number of clicks on the reveal button. A higher number of clicks reveals willingness to pay a higher non-monetary cost and thus implies stronger curiosity.

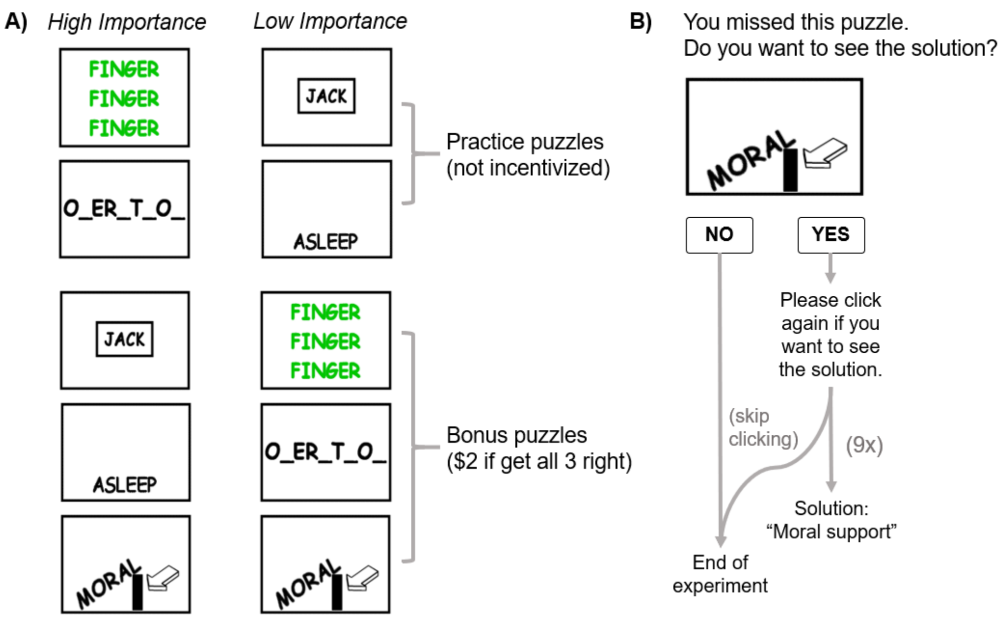
3.1.1 The Experiments

Experiment 1A: Importance. In the first experiment, we test whether increasing the perceived importance of an information gap affects demand to learn the solution to the puzzle. We manipulate attention toward the last puzzle by varying whether knowing the answer to this puzzle is important for obtaining the bonus. To do so, we vary the order in which the five puzzles are presented, effectively varying which puzzles are for practice and which count for payment (see Figure 1). The last (especially challenging) puzzle in the sequence ("moral support") is the same across treatments.

The two treatments thus attempt to vary whether knowing the solution to this last puzzle is pivotal for getting the bonus. In the *High Importance* treatment, two of the three bonus puzzles are easy to solve (90% and 83% managed to solve the "jack in the box" and the "falling asleep" puzzles in a pre-test, respectively), making the last puzzle usually pivotal, i.e., important for getting the $2 bonus. In the *Low Importance* treatment, the last puzzle follows two other challenging bonus puzzles (only 45% and 28% could solve the "green fingers" and the "painless operation" puzzles in a pre-test, respectively), typically making none of them pivotal (unilaterally important). The two practice puzzles in each treatment are the first two bonus puzzles from the other treatment, to ensure that participants in both treatments complete the same set of five puzzles, keeping the required effort and the overall difficulty constant.

We hypothesize that, conditional on failing to solve the last puzzle (and thus failing to get the bonus), the answer to the last puzzle is perceived as more important if it is the only answer that prevented one from winning the bonus (*High Importance* treatment) as opposed to being one of several answers that prevented individuals from getting the bonus (*Low Importance* treatment). We then predict that making this puzzle more important attracts more attention to the information gap regarding the correct answer to the puzzle, increasing the desire to find out the solution.

Figure 1. Experimental Procedure, Experiment 1A



Notes. Panel A shows the two experimental treatments of Experiment 1A: *High Importance* (left) and *Low Importance* (right). Panel B shows the behavioral measure used in Experiment 1A: the willingness to click to reveal the solution. If participants clicked 'YES' initially and clicked nine more times, the solution was revealed. If at any point they clicked 'NO', the experiment concluded without revealing the solution. This measure was the same across treatments.

According to the model, the answer to a pivotal puzzle is important because it has the chance to affect the final payoff. However, in our design, participants learn that they failed to receive the bonus right before being asked whether they want to find out the solution to the puzzle. Hence, finding out the solution cannot affect their payoff in any way. Yet, the assumption that importance does not change until a person adapts to a new belief implies that participants may still consider the answer important, even while recognizing that it no longer has instrumental value. So, we predict higher curiosity in the *High Importance* treatment than in the *Low Importance* treatment.

Experiment 1B: Salience. In the second experiment, we test the prediction that curiosity is stronger for information gaps that opened more recently and thus are more salient. In the experiment, participants complete two tasks on two consecutive days. On the first day, they work on the Rebus Puzzle Task as in Experiment 1A. They try two practice puzzles and can then earn a $2 bonus payment for correctly solving all three of the subsequent bonus puzzles. All participants face the same sequence of puzzles as in the *High*

Importance treatment of Experiment 1A. On the second day, participants answer a set of knowledge trivia questions, which serves as a filler task, unrelated to the puzzle task. As in Experiment 1A, participants have the option to exert effort to reveal the solution to the "moral support" puzzle, and curiosity is elicited the same way. To vary salience, we manipulate the timing of when participants are asked if they would like to reveal the solution. In the *Immediate* treatment, participants are asked immediately after completing the puzzle task on the first day whether they would like to reveal the solution immediately. In the *Delayed* treatment, participants are asked only on the second day, i.e., a day after completing the puzzle task, whether they would like to reveal the solution at that time. We predict that, conditional on failing to solve the "moral support" puzzle, participants will be more curious to learn the answer when this information gap is more salient, i.e., opened just before the opportunity to obtain the information, as opposed to a day earlier.[6]

Procedures. We recruited participants from Amazon Mechanical Turk. Participants received a fixed payment of $\$0.25$ for a 3-minute study, and had a chance to earn a $2 bonus if they solved all three bonus puzzles. In the Salience experiment (1B), we promised participants an additional $\$1.50$ for completing the second stage of the experiment a day after completing the first. The instructions for both experiments are available in Appendix B.

In both experiments, participants knew that their performance in the practice rounds did not affect their final payment. Upon enrollment, we randomly assigned participants in the Importance experiment (1A) to the *High Importance* or the *Low Importance* treatments, and participants in the Salience experiment (1B) to the *Immediate* or *Delayed* treatments. After completing the two practice puzzles and the three bonus puzzles, participants received feedback about their performance (how many of the practice and the bonus puzzles they solved correctly) and whether they won the bonus. In the Importance experiment and in the *Immediate* treatment of the Salience experiment, we then displayed the last (moral support) puzzle again and told participants whether they successfully solved it. Next, we elicited their curiosity by asking participants if they wanted to see the solution ('YES' or 'NO') and repeatedly asking this question if they clicked 'YES,' as described above. Participants who clicked the 'NO' button ended the study without revealing the solution. Since the puzzle comes in the form of an image, it was hard for participants to find the solution elsewhere (e.g., on the internet). In the Salience experiment, we invited participants in both treatments to the second stage via email the day after the first stage. In the second stage, participants worked on a set of trivia questions followed by some demographics questions. Their compensation did not depend on performance—they all received a fixed payment of $1.50. Whereas in the *Immediate* treatment participants were prompted to find out the solution of their last rebus puzzle ("moral support") at the end of stage 1, in the *Delayed* treatment we prompted participants to find out the solution one day later, at the end of stage 2.

3.1.2 Results

Experiment 1A: Importance. Eight hundred and fifty three participants (90.4%) completed the experiment. We excluded 15 participants (1.8%) who submitted duplicate responses. The final sample contained

[6]The *Delayed* treatment could also decrease the importance of the information gap—as time passes, participants may adapt to the fact that they did not win the bonus and they may then feel that the answer to the puzzle matters less to them. Still, the primary pathway for this manipulation to affect attention is likely that participants get distracted by other thoughts in the intervening 24 hours, i.e., through decreased salience.

838 participants (45.1% female): 418 in the *High Importance* treatment and 420 in the *Low Importance* treatment. We determined these sample sizes by conducting an a priori power analysis (see Appendix C).

Performance on the puzzle task. There was no significant difference in the proportion of people who failed to solve the "moral support" puzzle: 236 people (56.5%) missed this puzzle in the *High Importance* treatment and 239 (56.9%) missed it in the *Low Importance* treatment, $\chi^2(1, N = 838) = 0.004, p = .952$. Participants who failed to answer the "moral support" puzzle were able to solve significantly more bonus puzzles in the *High Importance* treatment, in which two easy puzzles preceded the last puzzle, $M = 1.66$, than in the *Low Importance* treatment, in which two hard puzzles preceded the last puzzle, $M = 0.49$, $t(469) = 19.619, p < .001$, Cohen's $d = 1.80$, 95% CI $[1.05, 1.22]$. In the *High Importance* treatment 183 people (77.5%) solved both bonus puzzles before the last puzzle, thus they missed their $2 bonus only because of missing the last puzzle. In the *Low Importance* treatment, 223 (93.3%) failed to solve at least one of the other two bonus puzzles before the last puzzle, missing the bonus because of missing multiple puzzles. In terms of overall performance, participants' total scores (practice + bonus) were not significantly different between the *High Importance*, $M = 2.03$, and the *Low Importance* treatments, $M = 2.08$, $t(467) = 0.532, p = .595$, Cohen's $d = 0.05$, 95% CI $[-0.23, 0.13]$. Similarly, there was no difference in total time spent trying to solve the puzzles (practice + bonus), $M = 2.82$ minutes in the *High Importance* treatment and $M = 3.05$ minutes in the *Low Importance* treatment, $t(466) = 1.085, p = .278$. Thus, the manipulation does not appear to have affected participants' effort, which suggests that treatment effects were driven by attention upon realizing the "moral support" puzzle was pivotal, as opposed to the effort put into solving it.

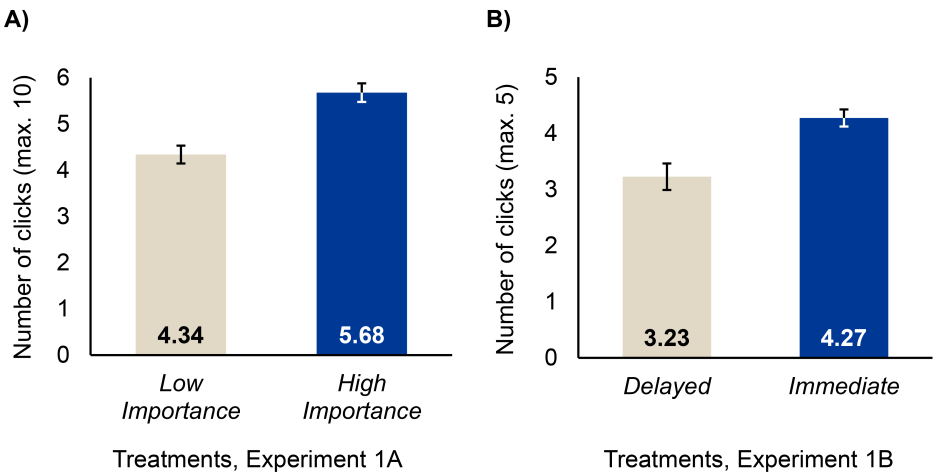
Main results: Willingness to exert effort to reveal the solution. Since the information gap of our interest existed only for those participants who could not answer the "moral support" puzzle—and not for those who managed to solve it—our key analyses focus on the group of people who failed to answer this puzzle correctly.[7] Out of the 475 participants who could not solve the "moral support" puzzle, only 32 (6.7%) declined to reveal the solution immediately—i.e., to click on 'YES' even a single time—and the average number of clicks was $M = 5.00$ ($SD = 3.10$). We report the detailed distribution of click counts by experimental treatment in Figure D1 in Appendix D.

Crucially, participants in the *High Importance* treatment clicked significantly more, $M = 5.68$, than in the *Low Importance* treatment, $M = 4.34$, $t(472) = 4.814, p < .001$, Cohen's $d = 0.44$, 95% CI $[0.79, 1.89]$ (see Figure 2A). Participants in the *High Importance* treatment were significantly more likely to start clicking to find out the solution, $M = 97.9\%$, compared to participants in the *Low Importance* treatment, $M = 88.7\%$, $\chi^2(1, N = 475) = 14.494, p < .001$, and to click the ten times to actually reveal the solution ($M = 25.4\%$ for *High Importance*, $M = 14.2\%$ for *Low Importance*, $\chi^2(1, N = 475) = 8.688, p = .003$).

We also investigate these results using OLS regression analyses. Table D1 in Appendix D shows that the overall number of clicks (column 1), the proportion of participants who clicked at all (column 3) and the proportion of participants who clicked ten times (column 5), were all significantly higher in the *High Importance* treatment. These results are robust to controlling for participants' total score, the time they

[7] Though not crucial for testing our theoretical predictions, we also analyzed the behavior of participants who correctly solved this puzzle. Unsurprisingly, they had little motivation to reveal the solution—that they already knew—and we do not find any significant effect of the experimental manipulation on their behavior. We report detailed test statistics in Appendix D.

Figure 2. Main Results, Experiments 1A–1B



Note. Error bars represent ± 1 standard error.

spent on each puzzle, and their gender (columns 2, 4 and 6). The total score and the time spent on the "moral support" puzzle also significantly predict the willingness to reveal the solution. These results are also consistent with our prediction regarding importance: The more invested people were—that is, the more effort they put into solving the puzzles—and the closer they got to solving all the puzzles, the more important the solution to the last puzzle was.

Experiment 1B: Salience. Two hundred participants (90.9%) completed the first stage of the experiment and were invited the next day to participate in the second stage. Of these, 74.5% ($n = 164$) completed the second stage. Among those who completed both stages of the experiment, we excluded seven duplicate responses (4.3%), leaving us with $n = 157$ observations (49.0% female). The proportion of participants who completed the second stage does not differ by treatments ($n = 77$ participants in the *Immediate* treatment and $n = 80$ participants in the *Delayed* treatment), $\chi^2(1, N = 200) = 0.119, p = .731$.

Performance on the puzzle task. There was no significant difference in the performance of participants between the two treatments: People solved on average 2.04 and 2.06 puzzles, in the *Immediate* and *Delayed* treatments, respectively, $t(154) = 0.183, p = .855$, Cohen's $d = 0.03$, 95% CI $[-0.28, 0.23]$. Across treatments, 108 people (68.8%) failed to solve the "moral support" puzzle. There was no significant difference in the proportion of people who failed to answer this puzzle correctly between the two treatments: 55 people (71.4%) missed this puzzle in the *Immediate* treatment and 53 (66.3%) missed it in the *Delayed* treatment, $\chi^2(1, N = 157) = 0.279, p = .598$.

Willingness to exert effort to reveal the solution. Out of the 108 participants who could not solve the "moral support" puzzle, only eight (7.4%) declined to click on "YES" even a single time, and the average number of clicks was $M = 3.76$ ($SD = 1.53$). We report the detailed distribution of click counts by experimental treatment in Figure D2 in Appendix D.

Key to our hypothesis, participants in the *Immediate* treatment clicked significantly more times, $M = 4.27$, than in the *Delayed* treatment, $M = 3.23$, $t(89) = 3.727, p < .001$, Cohen's $d = 0.72$, 95% CI $[0.49, 1.60]$ (see Figure 2B). Participants in the *Immediate* treatment were also significantly more likely to start clicking to find out the solution, $M = 98.2\%$, compared to participants in the *Delayed* treatment, $M = 86.8\%, p = .030$.[8] Finally, participants in the *Immediate* treatment revealed the solution (i.e., clicked five times) significantly more often, $M = 63.6\%$, compared to participants in the *Delayed* treatment, $M = 37.7\%$, $\chi^2(1, N = 108) = 6.246, p = .012$.

In Table D2 in Appendix D, we confirm these results using OLS regression, where we control for other factors that could potentially explain differences in the willingness to reveal the solution, such as the total score achieved, the time spent on the puzzles, and demographic covariates. The main results are robust to the inclusion of additional predictors. As in Experiment 1A, the total score and the time spent on solving puzzles also predict the willingness to reveal the solution. That is, the more effort people put into solving the puzzles, the more curious they were about the solution to the last puzzle.

Since our analyses were limited to the sample of participants who completed *both* stages of the experiment—as opposed to comparing everyone in the *Immediate* treatment who completed the first stage with the group of participants in the *Delayed* treatment who completed both stages—the difference in the willingness to reveal the solution between treatments cannot be explained by a selection effect. We also note that we do not find any evidence of a selection effect (see Figure D3, as well as additional analyses, in Appendix D).

3.1.3 Discussion

Experiments 1A and 1B provide support for the hypotheses that increasing the perceived importance and salience of an information gap increases demand for information (H1 and H2, respectively). The puzzle task allows us to isolate the curiosity motive from the motive to avoid negative information. However, these experiments rely on some non-trivial assumptions.

First, we assume that participants would not be able to find out the solution to the puzzle on their own by searching online. As discussed above, the puzzles are pictures, which made searching for their solutions difficult. But, if participants did somehow find the solution on their own in the *Delayed* treatment in Experiment 1B, this would have reduced their willingness to reveal the solution the next day, apart from any salience effect. Note, however, that the decrease in clicking in the *Delayed* treatment extends beyond the increased proportion who immediately decline to reveal the solution (see Figure D2 in Appendix D).

Second, in Experiment 1A we study information acquisition after the information loses its instrumental value, relying on the assumption that finding out the answer would not immediately cease to be important once a participant found out that they did not win the prize. This is likely a valid assumption because such hedonic adaptation is usually not instantaneous (Wilson et al., 2005), and we expected participants to continue to be curious about answers that were clearly important a moment ago.

To allay potential concerns that our findings rely on the validity of these assumptions, in Section 3.2 we report data from additional experiments in which we study demand for information using a different paradigm. In these experiments, participants can exert effort to learn ego-relevant information. This different paradigm allows us to manipulate importance without any additional assumption about adaptation, and to provide participants with information that they cannot obtain anywhere else. With this paradigm, we provide additional supportive evidence for hypotheses H1 (Experiment 2A) and H2 (Experiment 2B), showing the

[8] We report the significance value extracted from a Fisher's Exact Test, since the low expected frequencies violate the assumptions necessary for the Chi-square test. The corresponding Chi-square statistic with Yates correction would be 3.579, $p = .059$.

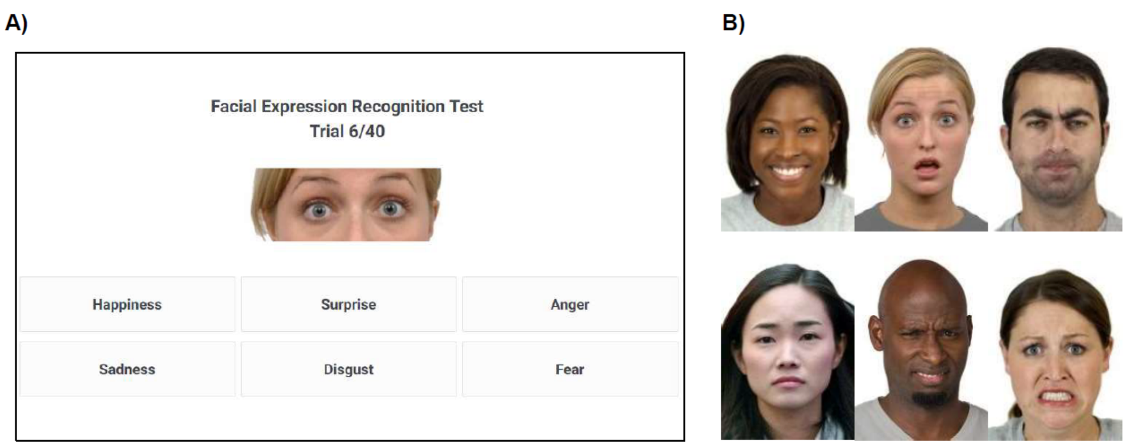
robustness of these effects in a domain where anticipated beliefs can be negative. This paradigm also allows us to test how valence affects information acquisition (Experiment 2C).

3.2 Ego-Relevant (Valenced) Information: The Facial Expression Recognition Test Paradigm

We now report data from three experiments that investigate demand for ego-relevant information, using a paradigm in which individuals can learn about their own performance on a test. In this domain, the curiosity motive may sometimes be overwhelmed by the desire to direct attention away from bad news. We first show that, even in this domain, directing attention to the information gap by making it feel more important or salient increases demand for information (Experiments 2A and 2B, respectively). Furthermore, we then show that the perceived valence of the information gap affects demand for information; individuals are more likely to acquire information when valence is more positive (Experiment 2C).

In these experiments, participants complete an online Facial Expression Recognition (FER) test we designed, which measures individuals' ability to recognize emotions from facial expressions. The FER test presents individuals with a sequence of 40 photos of faces, and asks them to guess which of six emotions (happiness, sadness, anger, disgust, fear, surprise) the people in the photos are displaying (see Figure 3 and Appendix B for the stimuli and detailed instructions).

Figure 3. The Facial Expression Recognition Test, Experiments 2A–2C



Notes. Panel A: Participants were shown cropped photos and had to guess which of the six emotions the person in the photo was experiencing. Panel B: A sample selection of six uncropped photos, representing the six emotions (happiness, sadness, anger, disgust, fear, surprise). We report the full list of photos in Appendix B.

By taking the FER test, participants activate an information gap about their ability to recognize emotions. Information about their performance may be ego-relevant if they want to believe they are good at recognizing emotions. We chose this test because we believe that participants have little prior knowledge about their ability to recognize emotions, and would naturally be curious about their performance. Importantly, they can obtain information about their score only in the course of the experiment, as this information is not available anywhere else (because we designed this unique test specifically for these experiments).

In order to reveal their scores, and thus, to close the information gap about their ability to identify emotions, participants have to complete an additional task for no extra payment. That is, after completing the FER test, participants have the opportunity to reveal their *exact* score and their relative ranking (percentile) compared to other participants by completing a boring 3-minute extra task. Participants receive no payment for the task; their only incentive is learning their score and relative ranking on the FER test. Revealing their exact score does not affect their payment in any way. We estimate curiosity by measuring the fraction of individuals who are willing to start and complete this extra task in order to learn their score.

3.2.1 The Experiments

Experiment 2A: Importance. In this experiment, we investigate how a manipulation of importance affects willingness to exert effort to learn about one's score on the FER test. Differently from Experiment 1A, in this experiment we manipulate importance by directly altering the size of a bonus participants can receive for doing well on the FER test. Prior to completing the task, participants learn that they will receive a bonus for correctly solving 50% of the task (20 out of 40 photos). A larger potential bonus makes their score more important because it makes participants care more about whether they get the bonus. After finishing the test, they are told that they will find out whether they got the bonus, and they are also given the option to work on the extra 3-minute task to learn their exact score. They know they will learn whether they got the bonus, regardless of their choice to learn their exact score, and getting this additional information cannot change whether they will get the bonus. Thus, we can identify demand for information about their exact score over and above their desire to know if they earned the bonus.

In the *High Bonus* treatment, the bonus is $\$1$. This bonus is on top of a $\$0.75$ fixed payment for completing the task. In the *Low Bonus* treatment, the bonus is $\$0.05$. We randomly assign *Low Bonus* participants to receive either the same fixed payment as participants in the *High Bonus* treatment ($\$0.75$) or a higher fixed payment of $\$1.70$. Conditional on scoring above threshold, participants in this *Low Bonus (high fixed pay)* treatment receive the same total earnings ($\$1.70 + \$0.05 = \$1.75$) as participants in the *High Bonus* treatment ($\$0.75 + \$1 = \$1.75$). We predict that the proportion of individuals who choose to start, and complete, the extra task to learn their exact score will be higher in the *High Bonus* than in the *Low Bonus* treatment.

To further support our theoretical predictions and to highlight the mechanism that drives information preferences, we include three manipulation check questions which we ask after the extra task but before participants learn their outcome (and exact score if they decided to complete the extra task). We ask how happy/unhappy (on a scale from -100 to $+100$) participants would feel a) if they got the bonus (U_{win}) and b) if they did not get the bonus (U_{lose}). Further we elicit beliefs about the likelihood of getting the bonus (p_{win}: 0–100%). These three measures allow us to calculate the *standard deviation* of the anticipated happiness (i.e., utility):

$$\mathrm{SD}(U) = \sqrt{(p_{win})(U_{win} - \bar{U})^2 + (1 - p_{win})(U_{lose} - \bar{U})^2},$$

where $\bar{U} = (p_{win})U_{win} + (1 - p_{win})U_{lose}$. According to our theory, the more spread out the distribution of possible utilities is (e.g., the higher the standard deviation of anticipated happiness), the more important the information gap is. If $\mathrm{SD}(U)$ is higher in the *High Bonus* treatment than in the *Low Bonus* treatments, then the experimental manipulation is successful, i.e., participants feel that their score is more important when they can win a larger bonus.

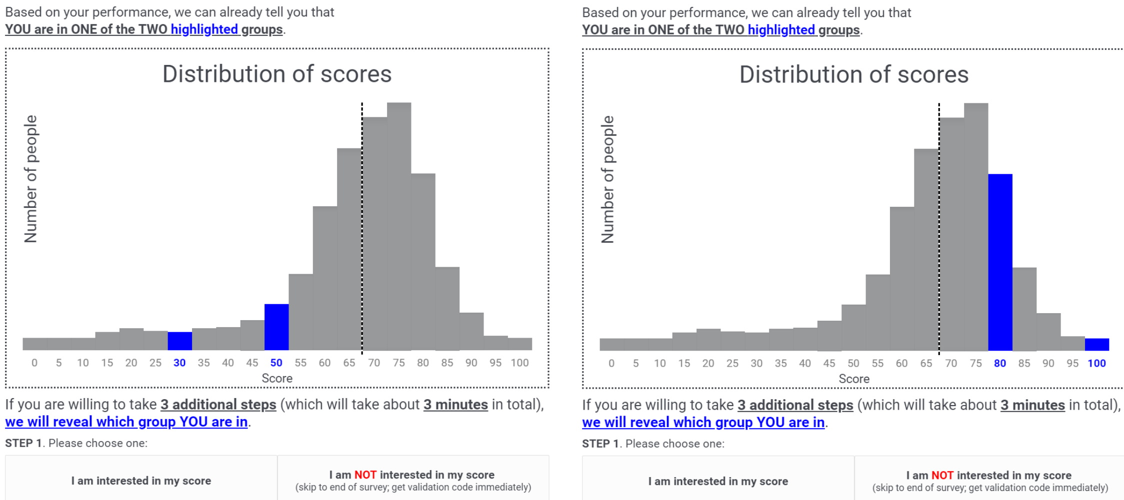
Experiment 2B: Salience. In this experiment, we use the FER paradigm to test the hypothesis that individuals are more curious about information gaps that were opened more recently, i.e., that are more salient. The experiment is similar to Experiment 2A, with the following exceptions: 1) Participants' performance on the test is not incentivized; 2) participants do not receive any immediate feedback on their performance. Instead, they receive a follow up email with an opportunity to complete an extra 3-minute task to learn about their performance on the FER test. The extra task does not result in any payment. As in Experiment 2A, participants are not forced to complete the extra task if they start it. However, if they quit, they do not receive *any* feedback about their score on the test. We manipulate salience by varying how recently the information gap is opened before the opportunity to complete the extra task. In the *Immediate* treatment, participants receive the email within 15 minutes after the FER test. In the *Delayed* treatment, participants receive it 24 hours after they complete the test. We predict that the proportion of individuals who choose to complete the test will be higher in the *Immediate* than in the *Delayed* treatment.

Experiment 2C: Valence. In this experiment, we use the FER test to investigate the prediction that people are willing to exert more effort to fill an information gap when the possible answers have more positive valence. To manipulate valence, we manipulate the difficulty of the task, thereby affecting participants' performance. In the *Easy* treatment, we oversample easy photos. In the *Hard* treatment, we oversample difficult photos. After performing the task, participants receive preliminary information about their performance. Specifically, we show participants the distribution of scores on a prior FER test of moderate difficulty, as well as the average score, and highlight two potential scores they could have gotten in the test, informing them that one of the two is (truthfully) their actual score. We manipulate whether the alternative score is 20 points higher or 20 points lower than the actual score. Depending on our treatments and their performance, three scenarios are possible: 1) *Good Expected News*: both scores are better than average (i.e., the participant could receive only good news by revealing which is the true score, Figure 4, right panel); 2) *Bad Expected News*: both score are worse than average (i.e., only bad news, Figure 4, left panel); or 3) *Mixed Expected News*: one score is at least average or better than that, while the other is at most average or worse than that (i.e., mixed news: either good or bad). While people may be naturally curious about their score in all three scenarios, varying the valence affects the motive to direct attention away from negative news (and toward positive news). After receiving the preliminary information, participants have the option to complete the 3-minute real effort task to find out which of the two highlighted scores is their actual score.

Procedures. We recruited participants on Amazon Mechanical Turk. In all experiments, participants received a fixed payment of $0.75 for completing the task, with the exception of half of the participants in the *Low Bonus* treatment, who received a $1.70 fixed payment instead. For each experiment, we determined the sample sizes by conducting an a priori power analysis; we report all power analyses in Appendix C.

In the Importance experiment (2A), which was pre-registered on aspredicted.org (LINK), on top of the fixed payment, participants received an additional bonus for successfully completing 50% of the task: $0.05 in the *Low Bonus* treatment and $0.75 in the *High Bonus* treatment. After completing the test but before learning whether they received the bonus, participants had the opportunity to reveal their exact score and their relative ranking (percentile) compared to other participants, by completing a boring 3-minute extra

Figure 4. Experimental Stimuli, Experiment 2C



Notes. The sample screens above depict the page where participants were told that their score is in one of the two highlighted bins, and were offered the opportunity to reveal their scores. Left: both the actual score and the alternative score are worse than average (Bad Expected News). Right: both the actual score and the alternative score are better than average (Good Expected News).

task. In this extra task, they had to guess the age of 15 people and indicate their confidence in their guesses. We included an attention check question at the end of the FER test. After the three manipulation check questions on anticipated happiness and probability of getting the bonus, we also included a comprehension check question testing whether participants understood that revealing (or not revealing) their score would not affect their payment. As pre-registered, we excluded participants who failed either the attention check or the comprehension check.

In the Salience experiment (2B), participants completed the FER test and did not receive any performance-based bonus. After completing the test they received a follow up email informing them of the opportunity to reveal their score. In the *Immediate* treatment, the email was sent within 15 minutes of completing the FER test. In the *Delayed* treatment, the email was sent 24 hours after participants completed the test. The email said: *"Thank you for taking the Facial Expression Recognition Test on [DATE]. Now you have the opportunity to learn your Facial Expression Recognition Score! If you are willing to take* 3 *additional steps (which will take about* 3 *minutes in total), we will reveal your FER Score, and you will also see how well you did compared to other people. To reveal your score, please open the link and follow the instructions: [LINK]."* In order to control for any time-of-the-day / day-of-the-week effects, we send these emails to everyone *at the same time*, but participants in different treatments *completed the FER test at different times*. After opening the link in the email, participants could complete the same 3-minute extra task as in Experiment 2A in order to learn their score on the FER test and their relative ranking (percentile) compared to other participants. There were no attention checks or comprehension questions in this experiment.

In the Valence experiment (2C), participants completed either an easy or hard version of the FER test (*Easy* and *Hard* treatment respectively). They were then shown the distribution of scores on an earlier (moderate difficulty) FER test, showing the proportion of people in each of the 21 score bins (0–100%, in 5% increments), also indicating the average score (see Figure B1 in Appendix B). Then, we highlighted two of these score bins, one of which contained their actual score, and another bin which contained an alternative score either 20 points higher or 20 points lower than their actual score.[9] Participants could then complete the same 3-minute extra task as in Experiments 2A and 2B to reveal which one was their score.

In all experiments, we measured the proportion of people who started and completed this task, and we also recorded participants' gender and age.

3.2.2 Results

Experiment 2A: Importance. Six hundred and thirty two participants completed the experiment. As pre-registered, we excluded 93 participants (14.7%) who failed the comprehension check question, 68 participants (10.7%) who failed the attention check question, and one participant (0.2%) who submitted a duplicate response. The final sample contained 470 participants (47.4% female, $M_{age} = 41.7$ years): 163 in the *High Bonus* treatment, 154 in the *Low Bonus (regular fixed pay)* treatment, and 153 in the *Low Bonus (high fixed pay)* treatment.

Manipulation checks and subjective importance. Consistent with our intended manipulation, participants reported higher expected happiness in relation to getting the bonus in the *High Bonus* treatment, $M = 76.2$, than in both the *Low Bonus (regular fixed pay)* treatment, $M = 44.5$, $t(283) = 8.781, p < .001$, Cohen's $d = 0.99$, 95% CI $[24.62, 38.84]$, and in the *Low Bonus (high fixed pay)* treatment, $M = 39.5$, $t(287) = 10.379, p < .001$, Cohen's $d = 1.18$, 95% CI $[29.75, 43.68]$. The expected happiness ratings upon getting the bonus were similar in the two *Low Bonus* treatments, $t(305) = 1.227, p = .221$, Cohen's $d = 0.14$, 95% CI $[-3.01, 12.98]$.

Similarly, participants reported that they would be significantly *less* happy if they *would not* get the bonus in the *High Bonus* treatment, $M = -42.8$, than in both the *Low Bonus (regular fixed pay)* treatment, $M = -13.6$, $(315) = 7.143, p < .001$, Cohen's $d = 0.80$, 95% CI $[-37.30, -21.19]$, and in the *Low Bonus (high fixed pay)* treatment, $M = -16.5$, $t(305) = 6.857, p < .001$, Cohen's $d = 0.77$, 95% CI $[-33.95, -18.81]$. Again, there was no significant difference in the happiness ratings between the two *Low Bonus* treatments, $t(299) = 0.774, p = .440$, Cohen's $d = 0.09$, 95% CI $[-4.42, 10.16]$.

Importantly, the experimental manipulation only affected participants' expectation about their (un)happiness upon getting (or not getting) the bonus, but not their expectation about the *likelihood* of winning: Participants reported that they would be equally likely to win in the *High Bonus* treatment, $M = 63.5\%$, as in the *Low Bonus (regular fixed pay)* treatment, $M = 64.4\%$, and in the *Low Bonus (high fixed pay)* treatment, $M = 65.6\%$. We observed no significant differences between any treatments, all $p > .392$.

Finally, we calculated $\mathrm{SD}(U)$ for each participant from the three measures reported above (p_{win}, U_{win}, and U_{lose}). Consistent with our intended manipulation, the subjective importance, as measured by $\mathrm{SD}(U)$, was significantly higher in the *High Bonus* treatment, $M = 49.0$, than in the *Low Bonus (regular fixed pay)* treatment, $M = 23.9$, $t(312) = 9.126, p < .001$, Cohen's $d = 1.02$, 95% CI $[19.70, 30.53]$, and in

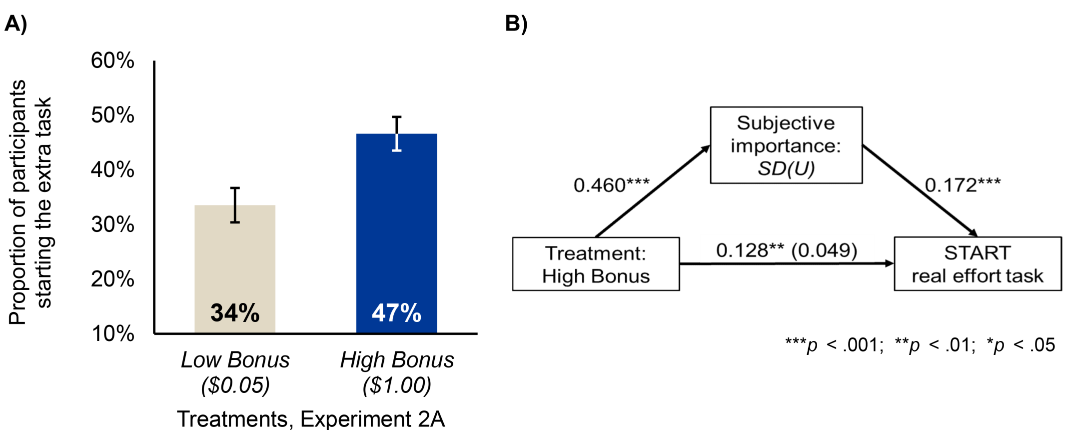
[9] This was randomized across participants: within both the *Easy* and *Hard* treatments, 50% of participants had an alternative score that was 20 points higher than their actual score, and 50% of participants had an alternative score that was 20 points lower than their actual score. If an alternative score would have been lower than 0% or higher than 100% as the result of the above calculation, we adjusted it to 0% or 100%, respectively. For those people who scored above 97% ($n = 8$), we always applied the -20 point adjustment to avoid having both scores in the same (21$^{\text{st}}$) score bin.

the *Low Bonus (high fixed pay)* treatment, $M = 21.7$, $t(312) = 9.78, p < .001$, Cohen's $d = 1.10$, 95% CI $[21.81, 32.79]$. There was no significant difference between the two *Low Bonus* treatments, $t(305) = 0.841, p = .401$, Cohen's $d = 0.10$, 95% CI $[-2.93, 7.31]$.

These manipulation checks confirm that the information about one's performance on the FER test in the *High Bonus* treatment was deemed to be more important than the same information in the *Low Bonus* treatments. In addition, we did not observe any significant differences between the two *Low Bonus* treatments, which indicates that participants treated the information as about equally important in both of these treatments. Therefore, we decided to pool these two treatments in subsequent analyses.[10]

Main results: Exerting Effort to See the Solution. A significantly higher proportion of participants started the extra task in the *High Bonus* treatment, $M = 46.6\%$, than in the *Low Bonus* treatments, $M = 33.6\%$ ($M_{regular} = 38.3\%$; $M_{high} = 28.8\%$), $\chi^2(1, N = 470) = 7.17, p = .007$ (see Figure 5A). Similarly, a significantly higher proportion of participants completed the extra task (and revealed their score) in the *High Bonus* treatment, $M = 42.3\%$, than in the *Low Bonus* treatments, $M = 30.9\%$ ($M_{regular} = 34.4\%$; $M_{high} = 27.5\%$), $\chi^2(1, N = 470) = 5.59, p = .018$.

Figure 5. Main Results and Mediation Analysis, Experiment 2A



Notes. Error bars in Panel A represent ±1 standard error. Coefficients in Panel B are standardized Beta coefficients.

To test whether the derived measure of subjective importance SD(U) predicts participants' decision to start and complete the extra task, as well as to control for potential wealth effects, actual performance, and demographic factors, we conducted hierarchical OLS regression analyses. In these models we included the proportion of people starting and completing the extra task as dependent measures, and added experimental treatment, subjective importance, level of fixed payment, actual score, age, and gender as potential predictors and covariates (see Table D3 in Appendix D).

This regression analysis revealed that the derived measure of subjective importance significantly predicts both whether someone starts and completes the extra task, $\beta = 0.003$, $SE = 0.001$, $t(467) = 3.377$, $p < .001$, and $\beta = 0.003$, $SE = 0.001$, $t(467) = 3.232$, $p = .001$, for starting and completing, respectively. Furthermore, this measure not only significantly predicts participants' choice to reveal their score, but adding this measure to the model makes the experimental treatment variable become non-significant, $p = .339$ and

[10]As a further robustness check, we control for the fixed pay amount in the regression analyses, see Table D3 in Appendix D.

$p = .464$, for starting and completing, respectively (Table D3, columns 2 and 5). Finally, the above results are robust to the inclusion of additional controls, including the amount of fixed pay, actual performance, and demographics (Table D3, columns 3 and 6).

Mediation analyses. As a final test of the proposed mechanism of subjective importance (i.e., spread of expected happiness), we conducted a mediation analysis to assess whether the effect of experimental condition on participants' desire to start and complete the extra task was mediated by the spread of their expected happiness. We included the experimental condition as the predictor variable and the proportions starting and completing the extra task as outcome variables. We then added $\mathrm{SD}(U)$ as the proposed mediator. All variables were standardized before conducting the mediation analysis. A bootstrapped mediation with $5,000$ replications revealed that subjective importance, $\mathrm{SD}(U)$, *fully* mediates the effect of experimental treatment on both starting and completing the extra task, $\beta = 0.080$, 95% CI [0.031, 0.132], $p < .001$ for starting the task (see Figure 5B) and $\beta = 0.076$, 95% CI [0.028, 0.130], $p < .001$, for completing the task.

Experiment 2B: Salience. Three hundred and ninety-eight participants completed the study (41.2% female; $M_{age} = 34.6$ years): 199 in the *Immediate* treatment and 199 in the *Delayed* treatment. We did not exclude any participants among people who completed the study.

Main results. Pooling across both treatments, 165 people (41.5%) opened the link in the email to start the extra task. To test whether the experimental manipulation had an effect on the willingness to start the extra task, we first compared the proportion of people who started the task *any time* after receiving the email. Note that we collected responses to the follow-up survey for *one week* after sending the follow-up emails, allowing the participants to start the extra task any time within one week following the test. The overwhelming majority of people (95%) who ever opened the link to the extra task, did so within the first 8 hours after receiving the follow-up email, and no one started the follow-up survey more than 2 days later than receiving the email.

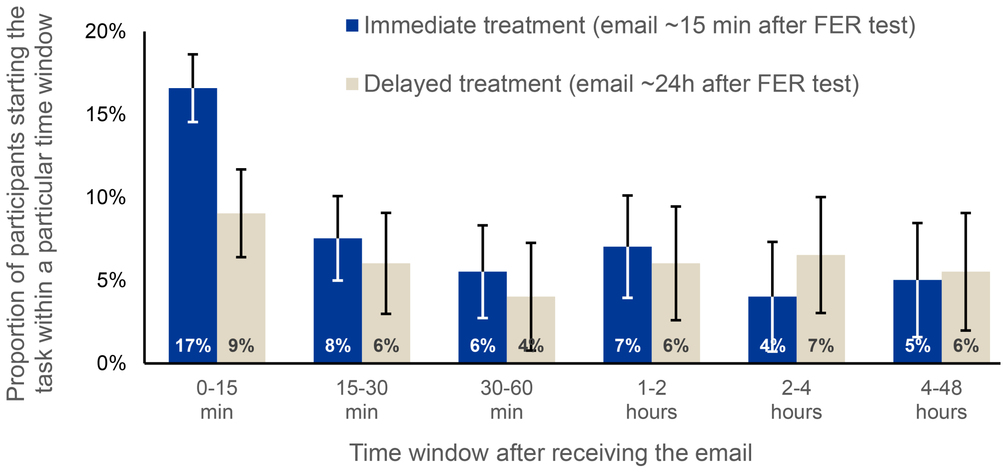
While 91 people (45.7%) started the extra task in the *Immediate* treatment, only 74 people (37.2%) did so in the *Delayed*, although this difference is not quite significant, $\chi^2(1, N = 398) = 2.650, p = .104$, Cohen's $w = 0.171$). Since some participants did not check their email right away, thereby experiencing significantly longer delays than the 15-minute delay we intended for them, we also repeat the analyses by comparing subsets of participants *from both treatments* who opened the study link within a specific length of time after receiving it. We expected a bigger difference between experimental treatments when examining shorter time frames—e.g., people opening the study link within the first hour after receiving the email, when the information gap was still likely to be salient in the *Immediate* treatment.

While 59 people (29.7%) started the extra task within one hour after receiving the email in the *Immediate* treatment, only 38 people (19.1%) did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 5.453, p = .020$, Cohen's $w = 0.211$. By contrast, when comparing the proportion of people who started the extra task *at least* one hour later after receiving the email, we do not find any significant difference—the proportions are virtually identical: 16.1% in the *Immediate* and 18.1% in the *Delayed* treatment, $\chi^2(1, N = 398) = 0.160, p = .690$.

The boundary between 'shorter' and 'longer' time frames is, however, somewhat subjective. We thus check the robustness of this result at different thresholds: 15 minutes, 30 minutes, 2 hours, and 4 hours.

Importantly, we obtain the same results if we set a different threshold: The proportion of people starting and completing the extra task is always higher in the *Immediate* treatment than in the *Delayed* treatment (we report the results of these analyses in Appendix D). These effects are almost entirely driven by the difference in the behavior of people who started the extra task within the earliest time window (within 15 minutes) after receiving the follow-up email (see Figure 6), which is consistent with the model's prediction that individuals are most curious when the information gap is the most salient.

Figure 6. Main Results, Experiment 2B



Note. Error bars represent ± 1 standard error.

In Table D4 in Appendix D, we report the results of OLS regressions that check the robustness of these results controlling for the FER score and demographic factors. These regression analyses confirm the findings reported here: Participants were significantly more likely to open the link in the email—and thus start working on the real effort task to reveal their FER test scores—in the *Immediate* treatment compared to those in the *Delayed* treatment, when we look at reasonably short time windows (any window within 2 hours), even after controlling for their performance and demographic factors.

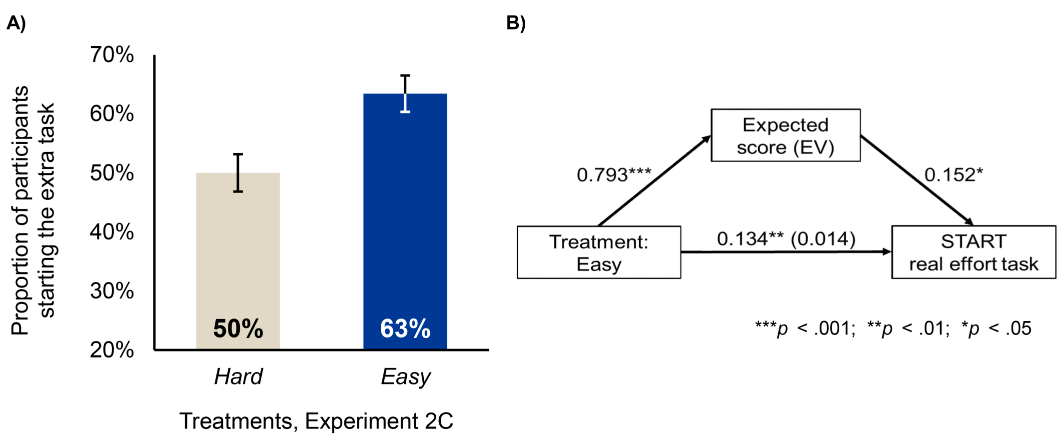
This result suggests that demand for information is higher when an information gap is more top-of-mind. While we cannot completely rule out that differential selection may play a role in this experiment, selection cannot fully account for this result. If participants in the *Delayed* treatment were busier at the time of receiving the email, but still just as curious, then we would expect them to have greater demand for information than in the *Immediate* treatment in *later* time windows (when they eventually catch up on their email). However, we do not see any catch-up effect for participants in the *Delayed* treatment. The proportion of participants starting the extra task in later time windows is virtually identical across treatments (see Figure 6), even though they had *a week* after receiving the email to complete the task and obtain the information. This supports our view that higher salience leads to stronger demand for this information.

Experiment 2C: Valence. Five hundred and one participants (94.5%) completed the experiment. We excluded three participants (0.6%) who submitted duplicate responses. The final sample contained 498 observations (55.2% female; M_{age} = 37.3 years): 246 participants in the *Easy* treatment and 252 participants in the *Hard* treatment.

Performance on the FER test and manipulation check. Participants scored significantly higher in the *Easy* treatment, $M = 83.2\%$, than in the *Hard* treatment, $M = 47.4\%$, $t(478) = 39.814, p < .001$, Cohen's $d = 3.56$, 95% CI $[33.99, 37.52]$. Consistent with actual performances, people in the *Easy* treatment guessed that they scored significantly higher, $M = 69.3\%$, than participants in the *Hard* treatment, $M = 59.4\%$, $t(494) = 6.410, p < .001$, Cohen's $d = 0.57$, 95% CI $[6.87, 12.94]$. These differences in both actual and expected scores ensured that the majority of participants faced different scenarios in the two treatments. In the *Easy* treatment 168 people (68.3%) had both scores above average, thus could receive good news only, 73 (29.7%) could receive mixed news, and only 5 (2%) could receive bad news only. By contrast, in the *Hard* treatment 163 (64.7%) could receive bad news only, 88 (34.9%) could receive either good or bad news, and only 1 person (0.4%) could receive good news only.

Main results: Willingness to exert effort to reveal score. First, we compared the proportion of people who started and completed the extra task to reveal their score between experiment treatments. Consistent with our predictions, significantly more people started the extra task in the *Easy* treatment, $M = 63.4\%$, than in the *Hard* treatment, $M = 50.0\%$, $\chi^2(1, N = 498) = 8.583, p = .003$ (see Figure 7A). Similarly, significantly more people completed the task in the *Easy* treatment, $M = 58.5\%$, than in the *Hard* treatment, $M = 43.7\%$, $\chi^2(1, N = 498) = 10.450, p = .001$.

Figure 7. Main Results and Mediation Analysis, Experiment 2C



Notes. Error bars in Panel A represent ± 1 standard error. Coefficients in Panel B are standardized Beta coefficients.

We also looked at the proportion of people who started and completed the extra task in both treatments, depending on whether they were facing good news only, bad news only, or mixed news. While only 78 out of 168 people (46.4%) started the extra task when facing bad news only, a marginally significantly larger proportion of people did so when facing mixed news, $M = 57.1\%$, $\chi^2(1, N = 329) = 3.362, p = .067$. The proportion of people starting the extra task was even higher among people who faced good news only: 112 out of 169 participants (66.3%). This proportion is significantly higher than the proportion in the bad news only scenario, $\chi^2(1, N = 337) = 12.695, p < .001$, but not significantly higher than in the mixed news scenario, $\chi^2(1, N = 330) = 2.538, p = .111$.

The results are similar if we look at the proportion of people completing the extra task, which was lowest among people who faced bad news, $M = 38.7\%$, followed by the mixed news scenario, $M = 54\%$, and was highest in the good news scenario, $M = 60.4\%$. The proportion in the bad news scenario was significantly lower than in the good news scenario, $\chi^2(1, N = 337) = 14.964, p < .001$, and was significantly lower than in the mixed news scenario, $\chi^2(1, N = 329) = 7.185, p = .007$. The proportion in the mixed news scenario was not significantly different from the proportion in the good news scenario, $\chi^2(1, N = 330) = 1.099, p = .295$.

These results are confirmed by OLS regression analyses that control for the total time spent on the FER test and demographics. In these analyses we also tested whether the expected score (i.e. the average of the two possible scores) predicts participants' willingness to start and complete the extra task (see Table D5 in Appendix D). Our theory predicts that people are more motivated to obtain information if they are expecting to learn good news, i.e., a positive relationship between expected score and willingness to reveal the actual score. Consistent with our theory, we found that expected score significantly predicts both the willingness to start and the willingness to complete the extra task, $\beta = 0.003$, $SE = 0.001$, $t(495) = 2.094$, $p = .037$, and $\beta = 0.004$, $SE = 0.002$, $t(495) = 2.636$, $p = .009$, for starting and completing, see Table D5 in Appendix D). Moreover, including expected score as a predictor makes the treatment dummy variable non-significant, both $p > .842$, which suggests that being assigned to the *Easy* or the *Hard* treatment only affects willingness to reveal the actual score through its effect on the expected score.

Mediation analyses. To test whether expected score mediates the effect of experimental manipulation on the willingness to start and complete the effort task, we conducted a mediation analysis. We included the experimental condition as the predictor variable and starting and completing the extra task as outcome variables. We added the expected score as the proposed mediator variable. All variables were standardized before conducting the mediation analysis. A bootstrapped mediation with $5,000$ replications revealed that the expected score *fully* mediates the effect of experimental condition on starting the extra task $\beta = 0.121$, 95% CI [0.006, 0.233], $p = .041$ (see Figure 7B). The results are similar when looking at the effect of experimental condition on completing the extra task, $\beta = 0.152$, 95% CI [0.039, 0.264], $p = .010$.

3.2.3 Discussion

The results of these experiments provide additional support for hypotheses H1 and H2, showing that, in an ego-relevant domain, higher perceived importance and higher salience increase demand for information (Experiments 2A and 2B, respectively). The ego-relevant domain also allows us to manipulate the valence of anticipated beliefs, confirming the prediction that demand for information is higher when the valence of expected news is more positive (hypothesis H3).

4 General Discussion

4.1 Additional Predictions about Curiosity

Our experiments confirm our theory's predictions that demand for information can be stimulated or inhibited by manipulating the importance of a question, the salience of a question, or the valence of the potential answers to a question. We also derive additional predictions that we do not test here, but that make sense of existing findings about curiosity.

Our theory predicts that another attentional factor, (recent) *surprise*, can stimulate curiosity too. If a person has previously received information addressing (but not completely resolving) a question, and has not yet adapted to his revised beliefs, curiosity about this question tends to be stronger than if no relevant information had been received (or than if adaptation had already occurred), and even stronger when the previously received information was more surprising. While we do not test for an effect of surprise in our experiments, this prediction is in line with existing evidence that being surprised stimulates curiosity about trivia questions (Loewenstein, 1994; Vogl et al., 2020). For example, people are more curious to find out the Easternmost state in the U.S.A. (which, surprisingly, happens to be Alaska) after getting separate feedback on each of three wrong guesses they made than after getting feedback all at once on three wrong guesses (Loewenstein, 1994). Similarly, incrementally revealing hidden information about the identity of the protagonist in a story keeps people more curious throughout the story (Law et al., 2016), and incrementally revealing attributes of a vacation package makes people more curious about it (Wright et al., 2018). The provision of each piece of information generates surprise and increases curiosity.

According to our theory, curiosity also depends on the expected *informativeness* of a piece of information, but only to the extent the information addresses specific questions attracting attention. People are more curious when they expect that information will more completely resolve an information gap, and people are especially motivated to acquire information that has the potential to fill multiple information gaps at once. Simultaneously resolving multiple information gaps generates an *epiphany*—a eureka moment of sudden comprehension. People may be especially curious when they anticipate a potential epiphany. Future work could test this prediction.

4.2 Implications for Information Avoidance

Our theory predicts that non-instrumental information tends to be desired when it addresses an activated question (i.e., an information gap), as long as a person anticipates non-negative beliefs (i.e., beliefs an individual does not mind thinking about). When filling an information gap poses no threat to utility, as would be true for answering a purely 'intellectual' question (e.g., whether a particular tree is an oak or an elm), people generally want the information. However, when acquiring information might lead to negative beliefs, individuals may choose to avoid this information.

Empirical studies have revealed strong evidence consistent with the idea that people tend to seek out information likely to confirm suspicions that their objective situation is favorable, and to avoid information most likely confirming that their objective situation is unfavorable. As the valence of anticipated outcomes becomes more negative, information avoidance becomes stronger (e.g., Ganguly and Tasoff, 2016; Charpentier et al., 2018). Bénabou and Tirole's (2002) model of self-confidence and Kőszegi's (2006) model of ego utility both make the opposite prediction. They predict that people would have greater desire for information about themselves when they hold negative beliefs about themselves than when they hold positive beliefs about themselves because information may prompt an individual to change a prior belief. While the logic is intuitive, the empirical research suggests that this is not typically the case.

According to our theory, preference about information that would more clearly resolve negative beliefs involves a trade-off between curiosity and the desire to not think about these negative beliefs. We predict that this trade-off may depend on the prior attention directed towards these beliefs (as well as how negatively valenced they are). If the marginal increase in attention due to surprise is independent of the salience and importance, then as the salience or the importance of a question increases, the threshold at which a person prefers to avoid information shifts to increasingly negative beliefs. Indeed, van Dijk and Zeelenberg (2007) and Falk and Zimmermann (2016) manipulate salience (in different ways) to affect willingness to obtain potentially negative information, in line with our prediction. Along these lines, many people may avoid medical tests to avoid thinking about the possibility of being sick, but when forced to reckon with it (e.g., when talking with a doctor about symptoms that cannot be ignored), they may then prefer to be informed of a diagnosis. In Appendix E, we use our theory to provide an alternative account of avoidance of medical testing in the context of genetic testing for Huntington's Disease (Oster et al., 2013).

4.3 The Belief Resolution Effect

According to our theory, the impact of new information on attention is greatest when uncertainty about a question is resolved completely. Surprise prompts an immediate spike in attention, but it fades with adaptation. The underlying question then becomes unimportant because, with the answer known, there is no longer a range of possible answers. The *belief resolution effect* refers to the dynamic pattern of attention that results from filling an information gap and then adapting to it. When an answer is learned with certainty, there is an immediate boost in attention weight on it, but after the person adapts, this attention weight falls.

A surprising feature of curiosity discussed in Loewenstein's (1994) review is that the pleasure one derives from obtaining information one is curious about often seems incommensurate (on the negative side) with the intensity of the drive to obtain the information. A juicy nugget of gossip is eagerly received but soon forgotten. This property is naturally accommodated by the belief resolution effect. The attention weight associated with a particular question initially rises when the definitive answer is learned, but ultimately falls below its prior level after a person adapts. The satisfaction of curiosity will be disappointing to the extent that this drop in attention weight occurs rapidly (as seems likely to be the case) and unexpectedly.

The belief resolution effect also implies that the ostrich effect for unpleasant information may be counterproductive to individual welfare. While people may avoid bad news because they do not want to think about it, the effect on attention is likely to reverse after people adapt. According to the belief resolution effect, after people adapt to new, definitive beliefs, surprise fades and certainty allows one to pay less attention to bad news, as it eventually seems less important. This can facilitate hedonic adaptation (e.g., Smith et al., 2009). So, it might be better initially to have definitive good news, and worse to have definitive bad news, but eventually the situation is likely to change because people adapt to both good and bad news, when it is definitive. While ignorance may be bliss, a persistent nagging doubt about the possibility of a negative state of affairs, such as a concern that one's child might be taking drugs, tends to be quite unpleasant. Our theory helps to explain why many people avoid confronting issues they don't like thinking about, and also predicts that people with greater foresight will be more likely to choose to obtain information about such issues.

The same situation, but in reverse, occurs for positive information. Uncertainty can prolong the pleasure of good news: Wilson et al. (2005) induced experimental subjects to experience a positive event (e.g., receive an unexpected gift of a dollar coin) under conditions of certainty or uncertainty (e.g., it was easy or difficult to make sense of the text on the card). Subjects' positive moods lasted longer in the uncertain conditions, although people were unaware that this would be the case. This lack of awareness suggests, first, that people are most likely to make decisions based on initial reactions (seeking news that clarifies positive beliefs and avoiding news relating to negative beliefs), and, second, that these decisions are unlikely to maximize long-term experienced utility.

To the extent that people *are* aware of adaptation to bad news, we should predict that people who are more far-sighted—who discount the future less—will be more prone to resolve uncertainty about negative events so as to 'take the hit' then get on with their lives. That, in fact, has been found—people with low time discounting (as measured by self-reported financial planning horizons) are more likely to undergo cancer screening (Picone et al., 2004), and Ho et al. (2021) observe a significant correlation between discount rates and information avoidance across a variety of domains. By the same token, we might also predict that people who are more short-sighted will be more prone to resolve uncertainty about positive events, enjoying the momentary pleasure, but shortening its duration.

5 Conclusion

In this paper we use a theory of utility from beliefs about information gaps to make sense of a wide range of phenomena involving the demand for, or in some cases the desire to avoid obtaining, information. The theory can be applied to understand the effectiveness of clickbait—headlines that raise salient questions and promise answers for those who click on them (Blom and Hansen, 2015; Venneti and Alam, 2018)—the backlash to mandatory disclosure of calorie information (Loewenstein et al., 2014), and the avoidance of medical tests (Thornton, 2008; Hertwig and Engel, 2020). The standard account of the economics of information, which assumes that information is desired only to the extent that it enhances decision making, leaves out many—if not most—of the diverse reasons why people seek out or avoid information, including pure curiosity and the desire to savor good news and avoid bad news. Economists have addressed some of these motives in isolation (e.g., Caplin and Leahy, 2001; Bénabou and Tirole, 2002; Brunnermeier and Parker, 2005; Kőszegi, 2006; Bénabou, 2013), but the information-gap theory developed and tested here integrates a wide range of these motives into a unified theory. Sharot and Sunstein (2020) also have offered a framework for fitting these motives together; our theory fits into their framework, but relies on more specific assumptions, and thus makes specific new testable predictions, which we show to be empirically supported.

Although our modeling relies on an extensive new apparatus, including the concepts of questions, answers and attention weights, it offers many new predictions. As detailed in Section 2.4, we predict that contextual factors that affect attention, such as the importance and the salience of an information gap, will affect the demand for (and avoidance of) information, as will the valence of potential beliefs. We find support for these predictions in our experiments. Consistent with existing empirical evidence, but not tested here, the model also predicts that providing some related information (especially if surprising) increases demand for information, and that there is greater demand for information that may fill more information gaps, as long as only non-negative beliefs are expected. In addition to these derived predictions, we can also identify some additional predictions that go beyond our formal modeling, but which follow conceptually from our underlying theory. First, individuals who anticipate adaptation and who discount the future less should be more likely to expose themselves to information relating to negative beliefs and less eager to obtain information relating to positive beliefs. Second, anticipation that receipt of information will occur, especially in a context that makes it highly salient, motivates people to invest (time, effort, or money) in increasing its expected valence.

The model also has implications about the hedonic consequences of information acquisition. These implications could in principle be tested if we had measures of hedonic states, which could take the form of self reports, facial coding, physiological measurements, or even brain activity scans (see, e.g., Ruan et al., 2018). First, to the degree that people do not anticipate the decline in attention after learning an answer (the belief resolution effect), satisfying curiosity is disappointing; the initial motivation to gain the information is disproportionate to the pleasure gained from it. Second, acquiring information relating to negative beliefs actually improves long-term well-being. In the case of positive beliefs, resolving uncertainty may actually shorten the duration of the enjoyment of the belief. Third, if one can anticipate that a latent, meaningful question has non-negative valence answers, then activating the question and learning the answer leaves one better off than not being aware of the question in the first place (Golman and Loewenstein, 2018a).

Our information-gap framework can help to shed light not only on information acquisition and avoidance but on other phenomena as well. In a companion paper (Golman et al., 2021) we argue that the information-gap concept also underlies an alternative account of risk and ambiguity preferences that is conceptually different from, and has different testable implications from, the usual account of risk preferences involving utility curvature and the usual account of ambiguity aversion involving vague probabilities. Salient information gaps can either increase or decrease preference for uncertain gambles depending on whether it is painful or pleasurable to think about the information one is missing.

The question of when people seek out or avoid information has gained importance in the internet age, with so much information available at our fingertips. Attention has become a highly valued and sought commodity (Simon, 1971; Davenport and Beck, 2001). Competing for consumers' attention, media organizations and digital marketing professionals have become ever-more clever about creating clickbait that opens information gaps and piques curiosity. Television producers have likewise mastered the art of ending episodes with "cliffhangers" that open information gaps and beckon the viewer on to the next episode in search of answers. Apps aiming to help patients manage health conditions and investors manage their finances seek to engage curiosity to overcome information avoidance (since such information is, inevitably, sometimes adverse). As these content creators, product developers, PR managers, and marketers all vie for consumers' attention, and as consumers must sift through (and sometimes resist) their appeals and policy makers must figure out how to promote legitimate information, they all can benefit from a better understanding of the theoretical underpinnings of information seeking and avoidance.

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Appendix A

Following Golman and Loewenstein (2018), we represent a person's state of awareness with a set of activated questions $\mathcal{Q} = \{Q_1, \ldots, Q_m\}$, where each question Q_i has a set of possible (mutually exclusive) answers $\mathcal{A}_i = \{A_i^1, A_i^2, \ldots\}$.[11] We let X denote a set of prizes. Denote the space of answer sets together with prizes as $\alpha = \mathcal{A}_1 \times \mathcal{A}_2 \times \cdots \times \mathcal{A}_m \times X$. A cognitive state can then be defined by a probability measure π defined over α (i.e., over possible answers to activated questions as well as eventual prizes) and a vector of attention weights $\mathbf{w} = (w_1, \ldots, w_m) \in \mathbb{R}_+^m$. A utility function is defined over cognitive states, written as $u(\pi, \mathbf{w})$.

Material outcomes may correlate with answers to activated questions (and the answer to one question may correlate with the answer to another). We can consider a marginal distribution π_i that specifies the subjective probability of possible answers to question Q_i or π_X that specifies the subjective probability over prizes. For a given question Q_i, we may refer to a pairwise dependent question Q_j as one for which $\pi_{ij} \neq \pi_i \cdot \pi_j$.

The attention w_i on question Q_i is assumed to be strictly increasing in, and to have strictly increasing differences in, the question's importance γ_i and salience σ_i as well as to be strictly increasing in the surprise δ_i associated with it. Salience σ_i is taken to be exogenous, and we assume that a question Q_i is activated if and only if it has positive salience $\sigma_i > 0$. To characterize the importance of question Q_i, we consider the probabilities of discovering any possible answer and the utilities that would result in each scenario. We assume that the importance γ_i of question Q_i is a function of the subjective distribution of utilities that would result from different answers to the question,

$$\gamma_i = \phi\left(\left\langle \pi_i^0(A_i),\, U\left(\pi^{A_i}, \mathbf{w}^{A_i} \mid \mathcal{S}\right)\right\rangle_{A_i \in \operatorname{supp}\left(\pi_i^0\right)}\right), \tag{7}$$

that increases with mean-preserving spreads of the distribution of utilities and that is invariant with respect to constant shifts of utility.[12] To specify the surprise associated with revised belief about question Q_i when the answer A_j to related question Q_j is learned, we assume that it is equal to relative entropy:

$$\delta_i(\pi_i^{A_j} || \pi_i^0) = \sum_{A_i \in \mathcal{A}_i} \pi_i^{A_j}(A_i) \, \log \frac{\pi_i^{A_j}(A_i)}{\pi_i^0(A_i)}.$$

An assumption that the marginal increase in attention due to surprise scales linearly in the degree of surprise guarantees that if successive pieces of information are acquired without adaptation between these actions, surprise accumulates additively.

We let $v_X(x)$ denote the value of prize $x \in X$ and $v_i(A_i)$ denote the valence of answer A_i to question Q_i. We can identify answers with positive (neutral / negative) valence by the defining property that increas-

[11] A state of awareness is distinct from a state of the world in a traditional state-space model in that the answers to the activated questions do not necessarily uniquely identify a single state of the world. There may be multiple states of the world consistent with a set of answers, and there is presumably an infinite set of latent questions that a person could, in principle, ask to distinguish these states of the world, but of which the person is not currently aware.

[12] According to our definition, importance depends on utility, which in turn depends on the attention weight, but importance also contributes to attention weight. This definition encompasses many sources of importance. Questions may be intrinsically important, meaning that utility is directly dependent on the answer. Similarly, questions may have implicit importance if one cares about the answer to a correlated question, i.e., if the answer reveals a clue about something else with underlying intrinsic importance. Questions may also be materially important, meaning that the prize correlates with the answer (and utility is dependent on the prize). Finally, questions may be instrumentally important if the answer affects decision making, i.e., carries instrumental value. To make the comparisons concrete, the outcome of a competition between a home team and a divisional rival would be intrinsically important; the outcome of a preseason tuneup game might be implicitly important for what it reveals about the home team's prospects for the coming year; the outcome of a game on which one has wagered, but otherwise does not care about, would be materially important; and the outcome of that preseason game might be instrumentally important if one is deciding whether to bet on the teams' upcoming games. Note that for an intrinsically important question, increasing the question's salience causes the answers to have a bigger impact on utility and thus can make the question more important, too.

ing attention on sure belief about this answer increases (does not affect / decreases) utility. To capture aversion to uncertainty, we make use of a common measure of the uncertainty about a particular question Q_i: the entropy of the subjective probability distribution over its answers, $H(\pi_i) = -\sum_{A_i \in \mathcal{A}_i} \pi_i(A_i) \log \pi_i(A_i)$ with the convention that $0 \log 0 = 0$ (Shannon, 1948; Cabrales et al., 2013).[13] We consider the utility function

$$u(\pi, \mathbf{w}) = \sum_{x \in X} \pi_X(x) v_X(x) + \sum_{i=1}^{m} w_i \left(\sum_{A_i \in \mathcal{A}_i} \pi_i(A_i) v_i(A_i) \; - H(\pi_i) \right). \tag{8}$$

The first term describes expected utility over prizes and the remaining terms describe the utilities of beliefs about each activated question, amplified by the attention weights on each of these questions. Golman and Loewenstein (2018) describe properties that characterize this utility function.

The non-standard elements of the utility function, attention weights and the entropy component, are the source of the two new motives for information acquisition and avoidance that we identify in Section 2.3, curiosity and motivated attention. Having utility decreasing in the entropy of a belief, in order to capture aversion to uncertainty, implies that for a fixed level of attention, utility of beliefs is convex, i.e., that curiosity is always positive. This follows from the fact that acquiring information always decreases expected entropy. Adopting the utility representation in Equation (8), we see that curiosity (as formalized in Equation (4)) comes from the expected reduction in entropy of uncertain beliefs, weighted by the attention placed on those beliefs.

Having utility depend on attention implies not only that curiosity can depend on attention, but also that people may want to manage their attention. The desire to (partially) control the attention weight on beliefs with positive or negative valence gives rise to motivated attention. It is straightforward to see in Equation (5) that motivated attention is increasing in the valences of possible answers because the updated attention weights (immediately upon acquiring new information) increase due to surprise. The extra attention weight amplifies the value of newly acquired beliefs, leading to a gain or loss in utility.

Proposition 1 *Suppose utility takes the form of Equation (8), and take as an ancillary assumption that the marginal increase in attention due to surprise is independent of the prior level of attention. Suppose, additionally, that there are no subsequent actions available to the decision maker (so that we can disregard the instrumental value of information). For a given question Q_i, each of the following conditions implies that $\hat{D}_i > D_i$ (i.e., the desire for information answering the question will be greater with the new (hatted) parameters):*

1. *we change the history of beliefs (but not present beliefs) such that for some pairwise dependent question Q_{j^*} (perhaps Q_i itself), we increase the recently accumulated surprise from δ_{j^*} to $\hat{\delta}_{j^*} > \delta_{j^*}$, while maintaining or increasing the importance of all pairwise dependent questions Q_j, $\hat{\gamma}_j \geq \gamma_j$;*

2. *for some pairwise dependent question Q_{j^*}, we increase the salience from σ_{j^*} to $\hat{\sigma}_{j^*} > \sigma_{j^*}$, while maintaining or increasing the importance of all pairwise dependent questions Q_j, $\hat{\gamma}_j \geq \gamma_j$;*

3. *we transform π to $\hat{\pi}$ by changing some prize $x^* \in X$ to $\hat{x}^*$ such that for all pairwise dependent questions Q_j, importance increases to $\hat{\gamma}_j \geq \gamma_j$ with at least one such inequality strict;*

4. *we transform π to $\hat{\pi}$ by changing some pairwise dependent answer $A^*_\nu \in \mathcal{A}_\nu$ (for which $\pi_{i\nu}(A_i, A^*_\nu) \neq \pi_i(A_i) \cdot \pi_\nu(A^*_\nu)$) to $\hat{A}^*_\nu$ such that it has higher valence $v_\nu(\hat{A}^*_\nu) > v_\nu(A^*_\nu)$ and for all pairwise dependent questions Q_j, we maintain or increase importance $\hat{\gamma}_j \geq \gamma_j$; or*

[13] The base of the logarithm in the entropy formula is arbitrary and amounts to a normalization parameter.

5. *we change a set of beliefs π to $\hat{\pi}$ such that for some question Q_ν with $v_\nu(\varpi_\nu) \geq 0$ for all $\varpi_\nu \in \Delta(\mathcal{A}_\nu)$, this question now becomes pairwise dependent rather than independent, and for all pairwise dependent questions Q_j, we maintain or increase importance $\hat{\gamma}_j \geq \gamma_j$.*

Proposition 1 implies that:

1. When present beliefs about a question are deemed more surprising (because they were previously unexpected and the person has not yet adapted), there will be stronger desire for information addressing it (i.e., answering a related question or perhaps the given question itself), holding all else equal.

2. Increasing the salience of a question will also increase the desire for information addressing it.

3. Increasing the (material) importance of a question (by changing the prizes that may be received, depending on the answer) will similarly increase the desire for information addressing it.

4. Changing a relevant answer to one with higher valence, while not decreasing the (intrinsic/implicit) importance of related questions, will do the same.

5. Increasing the number of related questions, about which beliefs are necessarily positive or at least neutral, also has the same effect.

An immediate implication of this result (Condition 5) is that a single independent question with uniformly non-negative valence answers attracts a positive desire for information, as this desire has necessarily increased from none at all.

Corollary 1 *Suppose, as in Proposition 1, that utility takes the form of Equation (8) and that there are no subsequent actions available to the decision maker. If belief about question Q_i is independent of other beliefs, $\pi = \pi_{-i} \cdot \pi_i$, and only answers with non-negative valence are considered possible, $v_i(A_i) \geq 0$ (and, of course, $\pi_i(A_i) < 1$) for all $A_i \in \mathrm{supp}(\pi_i)$, then information answering this question would be sought, $D_i > 0$.*

Proof of Proposition 1

Conditions 1, 2 and 3 imply that attention weight has been made stronger on some pairwise dependent question Q_{j^*}, $\hat{w}^0_{j^*} > w^0_{j^*}$, and no weaker on other pairwise dependent questions Q_j, $\hat{w}^0_j \geq w^0_j$. Similarly, condition 4 implies that the valence of some answer has increased while the attention weight on all pairwise dependent questions has not decreased. We can consider all four of these cases together, being careful to distinguish (if and) how $\hat{\pi}$ differs from π in each case. We can apply properties that characterize the utility function (see Golman and Loewenstein, 2018). First, using label independence, we define a transformed value with $\hat{v}_X(x^*) = v_X(\hat{x}^*)$ under condition 3 and $\hat{v}_\nu(A^*_\nu) = v_\nu(\hat{A}^*_\nu)$ under condition 4, allowing us to maintain $\hat{\pi} = \pi$. Using Equation (2) we then write

$$\hat{D}_i - D_i = \sum_{A_i \in \mathcal{A}_i} \pi^0_i(A_i) \left(\hat{u}(\pi^{A_i}, \hat{\mathbf{w}}^{A_i}) - u(\pi^{A_i}, \mathbf{w}^{A_i}) \right) - \left(\hat{u}(\pi^0, \hat{\mathbf{w}}^0) - u(\pi^0, \mathbf{w}^0) \right), \tag{9}$$

where the terms representing instrumental value have vanished by assumption. We expand the utility functions according to Equation (8) and group terms in a utility difference

$$\hat{u}(\pi, \hat{\mathbf{w}}) - u(\pi, \mathbf{w}) = \pi_X(x^*) \left(\hat{v}_X(x^*) - v_X(x^*)\right) + \hat{w}_\nu \, \pi_\nu(A^*_\nu) \left(\hat{v}_\nu(A^*_\nu) - v_\nu(A^*_\nu)\right) + \sum_{j=1}^{m} (\hat{w}_j - w_j) \Bigg(\sum_{A_j \in \mathcal{A}_j} \pi_j(A_j) v_j(A_j) - H(\pi_j) \Bigg).$$

The ancillary assumption that the marginal increase in attention due to surprise δ_j is independent of the salience σ_j and the importance γ_j tells us that $\hat{w}_j^{A_i} - \hat{w}_j^0 = w_j^{A_i} - w_j^0$ or equivalently $\hat{w}_j^{A_i} - w_j^{A_i} = \hat{w}_j^0 - w_j^0$. This allows us to extract a common factor of $\hat{w}_j^0 - w_j^0$ in the last term of the expansion of Equation (9):

$$\begin{aligned}\hat{D}_i - D_i \;=\; & \left(\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i)\, \pi_X^{A_i}(x^*) \;-\; \pi_X^0(x^*) \right) \left(\hat{v}_X(x^*) - v_X(x^*) \right) \;+ \\ & \left(\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i)\; \hat{w}_\nu^{A_i}\, \pi_\nu^{A_i}(A_\nu^*) \;-\; \hat{w}_\nu^0\, \pi_\nu^0(A_\nu^*) \right) \left(\hat{v}_\nu(A_\nu^*) - v_\nu(A_\nu^*) \right) \;+ \\ & \sum_{j=1}^m (\hat{w}_j^0 - w_j^0) \left(\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) \left(\sum_{A_j \in \mathcal{A}_j} \left(\pi_j^{A_i}(A_j) - \pi_j^0(A_j) \right) v_j(A_j) \;-\; H(\pi_j^{A_i}) + H(\pi_j^0) \right) \right).\end{aligned}$$

We now simplify by applying the law of total probability on each line. The first line vanishes entirely, and the second and third lines reduce to

$$\begin{aligned}\hat{D}_i - D_i \;=\; & \sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i)\, \pi_\nu^{A_i}(A_\nu^*) \left(\hat{w}_\nu^{A_i} - \hat{w}_\nu^0 \right) \left(\hat{v}_\nu(A_\nu^*) - v_\nu(A_\nu^*) \right) \;+ \\ & \sum_{j=1}^m (\hat{w}_j^0 - w_j^0) \left(H(\pi_j^0) - \sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) H(\pi_j^{A_i}) \right).\end{aligned}$$

In conditions 1, 2 and 3, $\hat{v}_\nu = v_\nu$, so the first line vanishes. Condition 4 specified that $v_\nu(\hat{A}_\nu^*) > v_\nu(A_\nu^*)$, and because surprise can only increase attention weight we know that $\hat{w}_\nu^{A_i} - \hat{w}_\nu^0 \geq 0$, with the inequality strict for some A_i (specifically, for the A_i satisfying $\pi_{i\nu}(A_i, A_\nu^*) \neq \pi_i(A_i) \cdot \pi_\nu(A_\nu^*)$). Thus, in condition 4 the sum in the first line is strictly positive. Conditioning on the answer A_i strictly decreases (in expectation) the entropy of the belief about a pairwise dependent question Q_{j^*}, i.e., $H(\pi_{j^*}^0) - \sum_{A_i} \pi_i^0(A_i) H(\pi_{j^*}^{A_i}) > 0$. With $\hat{w}_{j^*}^0 > w_{j^*}^0$ in conditions 1, 2 and 3, this second sum is strictly positive. (In condition 4, we know only that it is non-negative because the latter inequality is weak.) Thus, in all three of these conditions, $\hat{D}_i > D_i$.

We now turn to condition 5. It specifies that importance of pairwise dependent questions does not decrease. We have just shown that increased importance of some pairwise dependent question can only increase the desire for information. We now consider the case that importance, and thus the prior attention weight $\mathbf{w}^0$, has not been changed by the transformation $\pi \to \hat{\pi}$ specified by condition 5. Recognizing that $\hat{\pi}_j^0 = \pi_j^0$ for all j, we have $u(\hat{\pi}^0, \mathbf{w}^0) = u(\pi^0, \mathbf{w}^0)$ (again using Equation (8)), and the change in the desire for information simplifies as

$$\hat{D}_i - D_i \;=\; \sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) \; \left(u(\hat{\pi}^{A_i}, \hat{\mathbf{w}}^{A_i}) - u(\pi^{A_i}, \mathbf{w}^{A_i}) \right). \tag{10}$$

Only the updated belief about question Q_ν (conditioning on A_i) and the surprise associated with this belief differ under the transformation in condition 5, so

$$\begin{aligned}u(\hat{\pi}^{A_i}, \hat{\mathbf{w}}^{A_i}) - u(\pi^{A_i}, \mathbf{w}^{A_i}) \;=\; & \left(\hat{w}_\nu^{A_i} - w_\nu^{A_i} \right) v_\nu(\hat{\pi}_\nu^{A_i}) \;+ \\ & w_\nu^{A_i} \left(\sum_{A_\nu \in \mathcal{A}_\nu} \left(\hat{\pi}_\nu^{A_i}(A_\nu) - \pi_\nu^{A_i}(A_\nu) \right) v_\nu(A_\nu) \;-\; H(\hat{\pi}_\nu^{A_i}) + H(\pi_\nu^{A_i}) \right).\end{aligned}$$

Plugging this into Equation (10) and simplifying with the law of total probability, we obtain

$$\hat{D}_i - D_i \;=\; \sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) \; \left[\left(\hat{w}_\nu^{A_i} - w_\nu^{A_i} \right) v_\nu(\hat{\pi}_\nu^{A_i}) \;+\; w_\nu^{A_i} \left(H(\pi_\nu^{A_i}) - H(\hat{\pi}_\nu^{A_i}) \right) \right] \tag{11}$$

We know $\hat{w}_\nu^{A_i} \geq w_\nu^{A_i}$ because there may be surprise about question Q_ν after learning A_i when these questions are pairwise dependent, but there is no surprise about Q_ν when these questions are independent, and surprise only increases attention weight. Moreover, condition 5 specified that $v_\nu(\cdot) \geq 0$, so the first term inside the brackets in Equation (11) is nonnegative. When the questions are pairwise independent, conditioning on A_i does not change the belief about Q_ν, so $\pi_\nu^{A_i} = \pi_\nu^0 = \hat{\pi}_\nu^0$. Conditioning on the answer A_i strictly decreases (in expectation) the entropy of the belief about a pairwise dependent question, so

$$\sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) H(\hat{\pi}_\nu^{A_i}) \;<\; H(\hat{\pi}_\nu^0) \;=\; \sum_{A_i \in \mathcal{A}_i} \pi_i^0(A_i) H(\pi_\nu^{A_i}).$$

Thus, returning to Equation (11), we conclude $\hat{D}_i > D_i$. ∎

Proof of Theorem 1

Put together Equations (3)-(5) and cross off the terms that cancel. ∎

Appendix B: Experimental stimuli and instructions

Instructions (screenshots of survey screens)

In this section we report the full instructions and experimental stimuli in all five experiments.

(starts on next page)

EXPERIMENT 1A

Screen 1

Please enter your Mturk worker ID

Screen 2

Welcome to today's study!

In this experiment we will ask you to solve some puzzles similar to the one displayed below.

Example

Solution: **Overseas travel**

Screen 3

Solution: Overseas travel

Practice Task

First, you will solve 2 puzzles in a practice round.

Correctly solving these 2 puzzle will not affect your earnings in the experiment.

Bonus Task

After the practice task, you will be asked to solve 3 additional puzzles that will be graded for the opportunity to win a bonus.

Your payment

On top of the 0.25 for the HIT, you will be paid a **$2 bonus** if you correctly solve ALL 3 Bonus Task puzzles.

Please be careful to avoid typing errors so that we can correctly grade your responses.

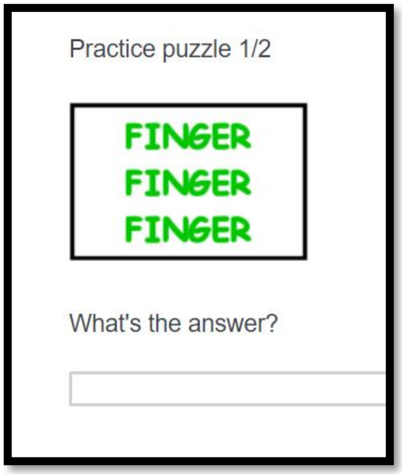
Screen 4

Practice Task

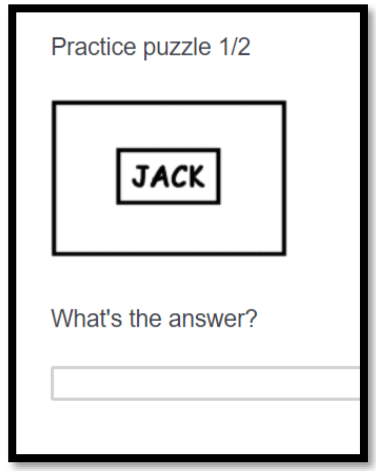
Solve the following two puzzles **for practice**.

Screen 5

HIGH IMPORTANCE treatment

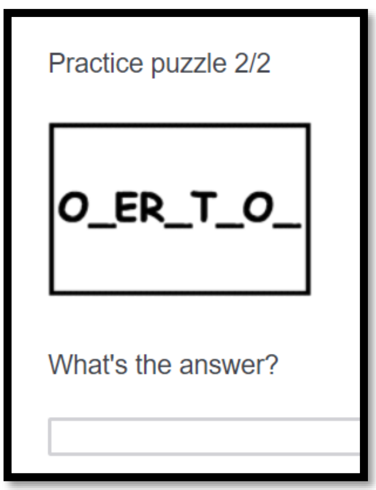


LOW IMPORTANCE treatment

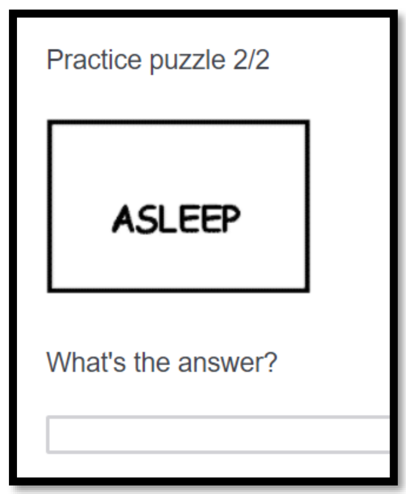


Screen 6

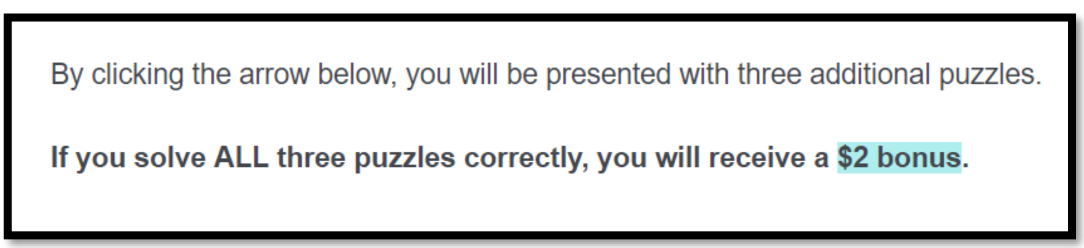
HIGH IMPORTANCE treatment



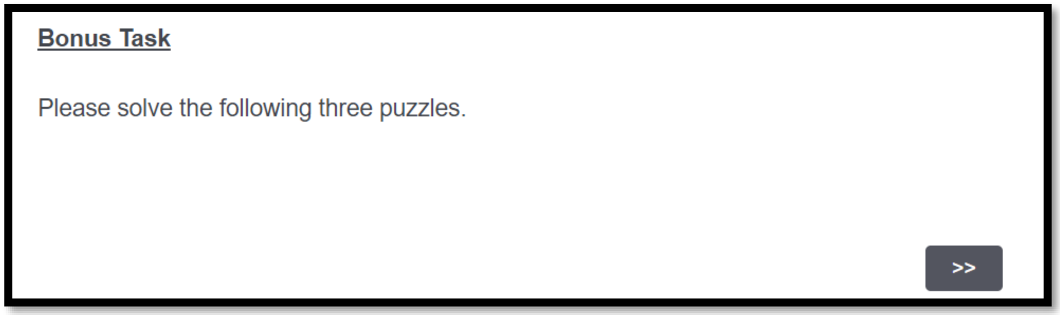
LOW IMPORTANCE treatment



Screen 7

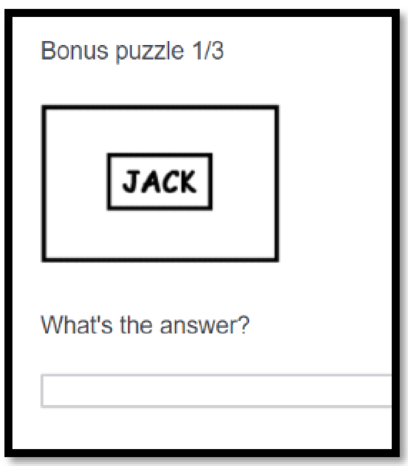


Screen 8

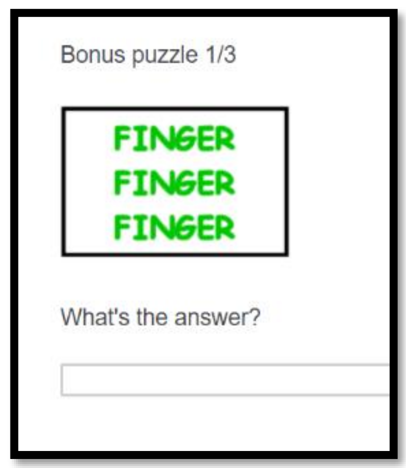


Screen 9

HIGH IMPORTANCE treatment

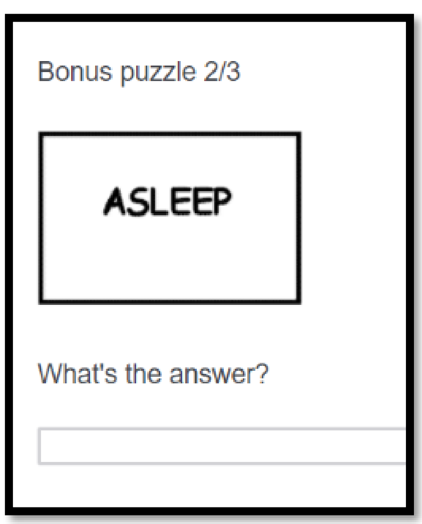


LOW IMPORTANCE treatment

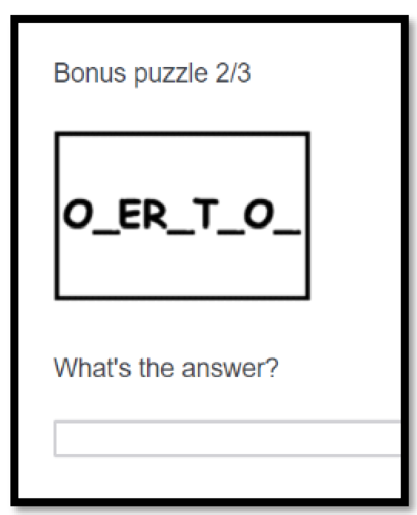


Screen 10

HIGH IMPORTANCE treatment



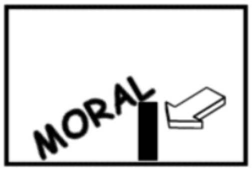
LOW IMPORTANCE treatment



Screen 11

[BOTH treatments]

Bonus puzzle 3/3



What's the answer?

Screen 12

[auto-advances after 3 seconds]

Calculating your score...

Loading..

Screen 13

[LEFT: failed to get bonus; RIGHT: got bonus]

Practice Task:
You solved **0 of the 2 practice** puzzles correctly.

Bonus Task:
You solved **0 of the 3 puzzles** correctly for the **bonus task**.

In order to get the $2 bonus, you had to solve all 3 puzzles correctly.

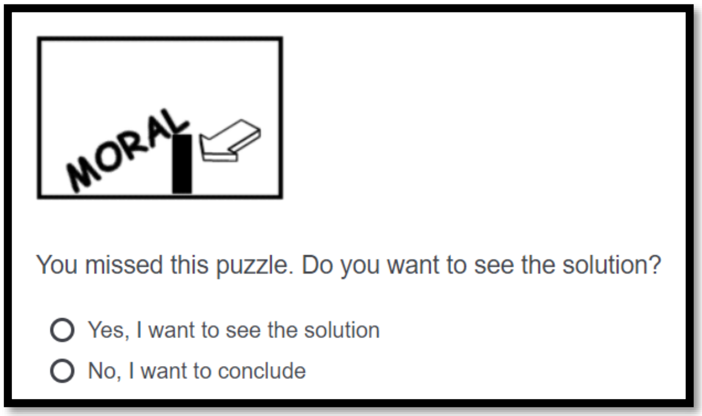
Practice Task:
You solved **0 of the 2 practice** puzzles correctly.

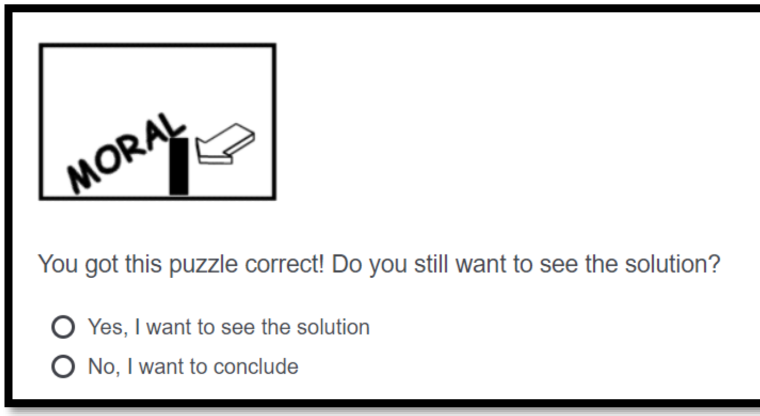
Bonus Task:
You solved **all 3 puzzles correctly for the bonus task**.

You will receive the $2 bonus.

Screen 14

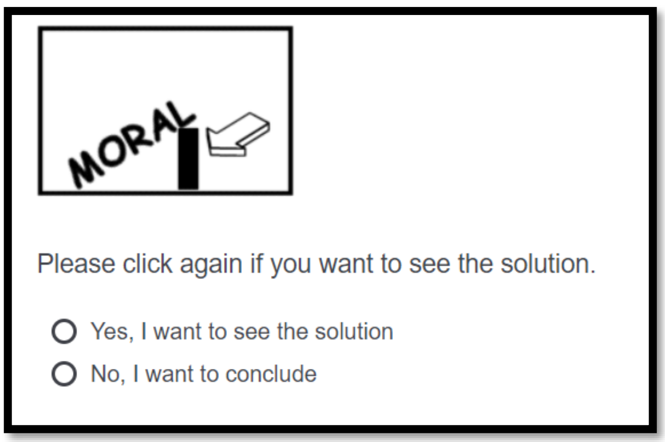
[LEFT: failed to solve ‘Moral Support’; RIGHT: solved ‘Moral Support’]





Screen 15

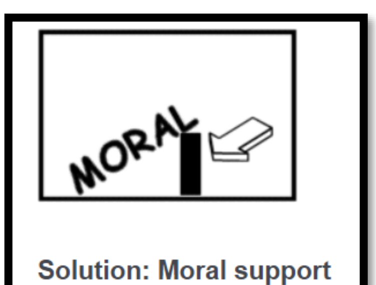
[displayed ONLY if participant selects ‘Yes’ in Screen 14]



[Screen 15 is repeated 9 times, unless the participant selects ‘No’]

Screen 16

[displayed ONLY if participant selects ‘Yes’ 9 times on Screen 15]



Screen 17

How difficult was this task?

Extremely easy	Moderately easy	Slightly easy	Neither easy nor difficult	Slightly difficult	Moderately difficult	Extremely difficult
○	○	○	○	○	○	○

Is English your native language?

Yes	No
○	○

You are:

Male	Female
○	○

Please specify your ethnicity. (you may select more if necessary)

- ☐ White/Caucasian
- ☐ African American
- ☐ Hispanic
- ☐ Asian
- ☐ Native American
- ☐ Pacific Islander
- ☐ Other (please specify) ________

(Optional) Please enter any comment you may have about the task

Screen 18

Thank you for your participation!

Your code for completing this HIT is: R_b8IBJVR30xXZLz3

IMPORTANT: Along with your Worker ID, this code is used to ensure you are paid for the work you did. Please copy and paste the code into the HIT box.

***** END OF EXPERIMENT 1A *****

EXPERIMENT 1B

Stage 1: Puzzles

Screen 1

Welcome to today's study!

In this experiment, you will need to solve some puzzles. You will receive $0.50 for the HIT and an additional bonus depending on your performance in the task.

Tomorrow, you will receive a link to a second part of the study. If you complete the second part of the study, you will receive an additional payment.

- ○ I understand that this is a two-part study and that I will be contacted tomorrow for participating in the second part. I agree to participate.
- ○ I no longer wish to participate in this study.

Screen 2

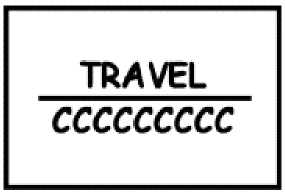
Please enter your MTurk ID below:

Screen 3

Puzzles.

Your task in this study is you to solve some puzzles similar to the ones displayed below.

Example:



Solution: **Overseas travel**

Puzzle Task

You are asked to solve 3 puzzles that will be graded for the opportunity to win a bonus.

Your payment

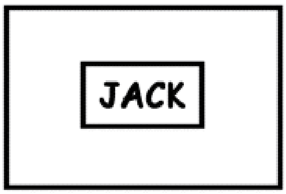
On top of the $0.50 for the HIT, you will be paid **a $2 bonus** if you correctly solve all 3 puzzles.

Please be careful to avoid typing errors so that we can correctly grade your responses.

Screen 4

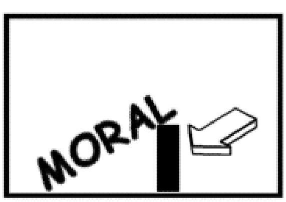
Puzzle Task:

Please solve the following puzzles.



what's the answer?

what's the answer?



what's the answer?

Screen 5

[If solved all three puzzles]

Puzzle Task: You solved all **3** puzzles correctly for the task. You will receive the $2 bonus.

[If solved fewer than three puzzles]

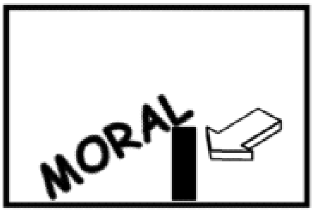
Puzzle Task: You solved **0** of the 3 puzzles correctly for the task. In order to get the $2 bonus, you had to solve all 3 puzzles correctly.

Screen 6

[Screens 6-8 were displayed only in the **IMMEDIATE** treatment.

In the DELAYED treatment, Screen 9 was displayed after Screen 5]

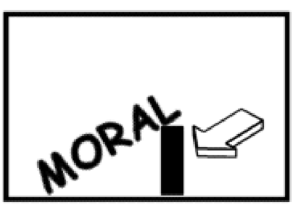
[if did NOT solve the ‘moral support’ puzzle]



In the puzzle task, you missed this puzzle. Do you want to see the solution?

- ◯ Yes, I want to see the solution
- ◯ No, I want to conclude

[if solved the ‘moral support’ puzzle]

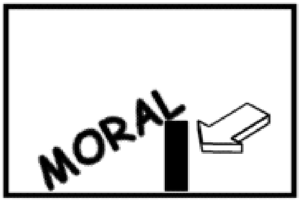


In the puzzle task, you got this puzzle correct! Do you still want to see the solution?

- ◯ Yes, I want to see the solution
- ◯ No, I want to conclude

Screen 7

[displayed only if selected 'YES' on Screen 6]



Please click again if you want to see the solution.

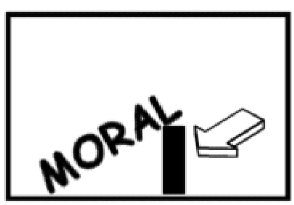
- ◯ Yes, I want to see the solution
- ◯ No, I want to conclude

[repeated 4 times if selected 'YES']

Screen 8

[displayed only if selected 'YES' 4 times on Screen 7]

Solution: Moral support



Screen 9

Please enter any comment you may have about the task

How difficult was this task?

Extremely easy	Moderately easy	Slightly easy	Neither easy nor difficult	Slightly difficult	Moderately difficult	Extremely difficult
○	○	○	○	○	○	○

Is English your native language?

- ○ Yes
- ○ No

If not, how fluent are you in english?

1 Not at all	2	3	4	5	6	7 Very fluent
○	○	○	○	○	○	○

Gender

Male	Female
○	○

Please specify your ethnicity.

- ○ White/Caucasian
- ○ African American
- ○ Hispanic
- ○ Asian
- ○ Native American
- ○ Pacific Islander
- ○ Other

Screen 10

Thank you for participating in this HIT! If eligible, you will receive your bonus within 7 days.

Tomorrow, you will receive an email invitation to participate in an additional HIT.

Click below to end the HIT and get access to your completion code.

Screen 11

Thank you for your participation!
Your code for completing this HIT is: R_23UedKwOpxAFTGI
IMPORTANT: Along with your Worker ID, this code is used to ensure you are paid for the work you did.
Please copy and paste the code into the HIT box.

*** END OF STAGE 1 ***

STAGE 2: TRIVIA

Screen 1

Welcome to the study.

In the part of the experiment, you will be asked to answer trivia questions in different categories presented in random order: Art and Literature, Sports and Games, Math, Verbal, and General Knowledge. There are 10 questions per section.

For each section, try to do your best in answering the questions. Do not leave the qualtrics screen at anytime during the task. You will have 3 minutes for each section of the study.

You will be paid a fixed fee of **$1.50** for the HIT. **We encourage you to do your best in all questions**. Note that you will not receive the bonus if you leave the study before the end.

Note that your average performance in one or more categories may be shared with another anonymous participant. If this happens, your identity will not be disclosed to the other participant.

Screen 2

Please enter your Mturk ID

Screens 3-7 contain the trivia questions.

Both the order of the five topics (general knowledge, art, sports, math, verbal),

and the order of questions within each topic were randomized.

Screen 3

02 50

GeneralKnowledge: Which of the following is not a country in Europe?

- ○ Germany
- ○ Spain
- ○ Poland
- ○ Italy
- ○ Mexico

GeneralKnowledge: How many runs did Sachin Tendulkar score in test cricket?

- ○ 15,921
- ○ 14,321
- ○ 20,089
- ○ 12,495
- ○ 14,639

GeneralKnowledge: Which volcano is best known for its eruption in AD 79 that led to the destruction of the Roman cities of Pompeii and Herculaneum?

- ○ Mount Etna
- ○ Mount Stromboli
- ○ Mount Vesuvius
- ○ Mount Vulture
- ○ Mount Loa

Screen 3 (cont.)

GeneralKnowledge: The reactor at the site of the Chernobyl nuclear disaster is now in which country?

- Ukraine
- Slovakia
- Hungary
- Russia
- Lithuania

GeneralKnowledge: What is the Judicial capital of South Africa?

- Cape Town
- Pretoria
- Johannesburg
- Durban
- Bloemfontein

GeneralKnowledge: Who is the current president of the United States of America?

- Barack Obama
- Bill Clinton
- Donald Trump
- Britney Spears
- Ronald Reagan

Screen 3 (cont.)

GeneralKnowledge: What is the third last number in the following sequence of numbers: 1, 22, 44, 66, 88, 100

- ○ 120
- ○ 150
- ○ 22
- ○ 66
- ○ 100

GeneralKnowledge: Which of the following countries has the largest population?

- ○ Mexico
- ○ Australia
- ○ Germany
- ○ China
- ○ Italy

GeneralKnowledge: In which city is the Eiffel Tower located?

- ○ France
- ○ Brussels
- ○ Rome
- ○ Berlin
- ○ Paris

GeneralKnowledge: How many goals did Alan Shearer score in the English Premier League?

- ○ 153
- ○ 187
- ○ 298
- ○ 260
- ○ 201

Screen 4

02 56

ART&LIT: What 1928 novel by D.H. Lawrence was banned in the U.S. until 1959?

- ○ Brave New World
- ○ The Catcher in the Rye
- ○ Lolita
- ○ Sons and Lovers
- ○ Lady Chatterley's Lover

ART&LIT: Roman floors often had decorations in

- ○ mosaics
- ○ terracotta
- ○ fresco
- ○ carved wood
- ○ paneled wood

ART&LIT: What Jane Austin novel includes the famous line: “It is a truth universally acknowledged that a single man in possession of a good fortune, must be in want of a wife”?

- ○ Sense and Sensibility
- ○ Mansfield Park
- ○ Pride and Prejudice
- ○ Emma
- ○ Little Women

ART&LIT: What city provides the setting for The Phantom of the Opera?

- London
- New York
- Paris
- Rome
- Venice

ART&LIT: Who painted the Sistene Chapel ceiling?

- Rafael
- Leonardo da Vinci
- Donatello
- Bellini
- Michelangelo

ART&LIT: What flowers was Monet most famous for painting?

- Roses
- Orchids
- Violets
- Water Lilies
- Irises

Screen 4 (cont.)

ART&LIT: What's the Shakespeare play if "All the world's a stage"?

- Hamlet
- Romeo and Juliet
- A Midsummer Night's Dream
- Much Ado About Nothing
- As You Like It

ART&LIT: Which Dickens character asked for more?

- The Artful Dodger
- Tiny Tim
- Miss Havisham
- Nicholas Nickleby
- Oliver Twist

ART&LIT: Who painted the ceiling of the Paris Opera?

- Marc Chagall
- Thomas Cole
- Umberto Boccioni
- Marcel Duchamp
- Jackson Pollock

ART&LIT: What war do the girls in Little Women grow up during?

- American Revolution
- World War I
- World War II
- Civil War
- Vietnam War

0249

SPORTS&GAMES: Who steers the shell and motivates the rowers in a crew race?

- Coxswain
- Sculler
- Sweep
- Rigger
- Stern

SPORTS&GAMES: What National Hockey League player scored the most career points?

- Wayne Gretzky
- Gordie Howe
- Mario Lemieux
- Bobby Orr
- Steve Yzerman

SPORTS&GAMES: What Pittsburgh Steelers quarterback held a national schoolboy record in the javelin?

- Terry Bradshaw
- Kordell Stewart
- Hienz Ward
- Boomer Esiason
- Phil Simms

Screen 5 (cont.)

SPORTS&GAMES: In polo, what is a period of play called?

- quarter
- chukka
- half
- set
- round

SPORTS&GAMES: Who was the first NBA draft pick in 2010?

- Greg Oden
- John Wall
- Derrick Rose
- LeBron James
- Kyrie Irving

SPORTS&GAMES: What distance is covered by the Olympic sprinter dubbed "the fastest man in the world"?

- 10 m
- 40 yds
- 50 m
- 100 m
- 200 m

Screen 5 (cont.)

SPORTS&GAMES: How many weeks encompass the three races of The Triple Crown of horse racing?

- ○ 3
- ○ 10
- ○ 5
- ○ 52
- ○ 12

SPORTS&GAMES: Which of these NHL teams is from New Jersey?

- ○ Ducks
- ○ Flames
- ○ Devils
- ○ Jets
- ○ Rangers

SPORTS&GAMES: Who ran the first four minute mile?

- ○ Roger Bannister
- ○ James Kwambai
- ○ Roger Ramjet
- ○ Roger Moore
- ○ Steve Prefontaine

SPORTS&GAMES: What tennis player was listed as the world's highestearning female athlete at the start of 2006?

- ○ Anna Kournikova
- ○ Serena Williams
- ○ Maria Sharapova
- ○ Venus Williams
- ○ Lindsay Davenport

Screen 6

02 51

MATH: Helpers are needed to prepare for the fete. Each helper can make either 2 large cakes per hour, or 35 small cakes per hour. The kitchen is available for 3 hours and 20 large cakes and 700 small cakes are needed. How many helpers are required?

- 10
- 15
- 20
- 25
- 30

MATH: A cubical block of metal weighs 6 pounds. How much will another cube of the same metal weigh if its sides are twice as long?

- 48
- 32
- 24
- 18
- 12

MATH: A straight fence is to be constructed from posts 6 inches wide and separated by lengths of chain 5 feet long. If a certain fence begins and ends with a post, which of the following could not be the length of the fence in feet? (12 inches = 1 foot)

- 17
- 28
- 35
- 39
- 50

MATH: Which of the following circles has the greatest number of points of intersection with the parabola $x^2 = y + 4$?

- $x^2 + y^2 = 1$
- $x^2 + y^2 = 2$
- $x^2 + y^2 = 9$
- x2 +y2 =16
- x2 +y2 =25

MATH: $2^{30} + 2^{30} + 2^{30} + 2^{30} =$

- 8^120
- 8^30
- 2^32
- 2^30
- 2^26

MATH: If V and W are 2dimensional subspaces of R^4 , what are the possible dimensions of the subspace spanned by the intersection of V and W?

- 1 only
- 2 only
- 0 and 1 only
- 0, 1, and 2 only
- 0, 1, 2, 3, and 4

MATH: If Logx (1 / 8) = - 3 / 2, then x is equal to

- -4
- 4
- 1/4
- 1/16
- 8

MATH: In a class of 78 students, 41 are taking French, and 22 are taking German. Of the students taking French or German, 9 are taking both courses. How many students are not enrolled in either course?

- 6
- 15
- 24
- 33
- 54

MATH: If an object travels at five feet per second, how many feet does it travel in one hour?

- 30
- 300
- 720
- 1800
- 18000

MATH: What is the average (arithmetic mean) of all the multiples of ten from 10 to 190 inclusive?

- 90
- 95
- 100
- 105
- 110

Screen 7

02 50

VERBAL: Please select the word(s) that best complete the sentence below:

Some fans feel that sports events are ____only when the competitors are of equal ability, making the outcome of the game____.

- ○ successful . . assured
- ○ boring . . questionable
- ○ dull . . foreseen
- ○ interesting . . predictable
- ○ exciting . . uncertain

VERBAL: Please select the answer that best replaces the underlined portion of the text below:

In similarity with some other great works, the enduring horror tale Frankenstein was first published anonymously; its author, Mary Shelley, wrote the novel when she was not quite nineteen years old.

(note that the first choice is the same as the original)

- ○ In similarity with
- ○ As
- ○ Like what happened with
- ○ Like the case with
- ○ Like

Screen 7 (cont.)

VERBAL: Please select the answer that best replaces the underlined portion of the text below:

New Zealand's Kaikoura Peninsula, a ruggedly beautiful spit of land, borders an undersea canyon that is home to the sperm whale and the giant squid. (note that the first choice is the same as the original)

- ○ borders an undersea canyon that is
- ○ bordering an undersea canyon,
- ○ and it borders an undersea canyon, which is
- ○ which borders an undersea canyon,
- ○ is the border of an undersea canyon, being

VERBAL: Please select the word(s) that best complete the sentence below:

The politician's speech to the crowd was composed of nothing but _____, a bitter railing against the party's opponents.

- ○ digressions
- ○ diatribes
- ○ platitudes
- ○ machinations
- ○ acclamations

VERBAL: Please select the word(s) that best complete the sentence below:

Because drummer Tony Williams paved the way for later jazzfusion musicians, he is considered a _____ of that style.

- ○ connoisseur
- ○ revivalist
- ○ beneficiary
- ○ disparager
- ○ progenitor

VERBAL: Please select the answer that best replaces the underlined portion of the text below:

The book is useful because it offers not just philosophy and theory <u>but also tells you what and how to live every day</u>.

(note that the first choice is the same as the original)

- ○ but also tells you what and how to live every day
- ○ but also it gives ways of everyday living
- ○ but also advice for everyday living
- ○ but also it gives practical advice for everyday life
- ○ and also tells you what to do and how to live every day

VERBAL: Please select the answer that best replaces the underlined portion of the text below:

Zookeepers <u>have expanded one's definition of care to include</u> concern for the animal's mental state as well as for its physical wellbeing. (note that the first choice is the same as the original)

- ○ have expanded one's definition of care to include
- ○ have expanded one's definition of care, including
- ○ expand their definition of care, they include
- ○ expanding the definition of care to include
- ○ have expanded their definition of care to include

Screen 7 (cont.)

VERBAL: Please select the word(s) that best complete the sentence below:

Alfred Schnittke's musical compositions are _____: phrases are clipped, broken into sections, and split apart by long rests.

- garnished
- improvisational
- fragmented
- cautious
- uniform

VERBAL: Please select the answer that best replaces the underlined portion of the text below:

<u>The time and the place for such a large event is subject to approving from the mayor's office.</u> (note that the first choice is the same as the original)

- The time and the place for such a large event is subject to approving from the mayor's office.
- For such a large event, the time and the place are subject to the mayor's office's approving them
- The time and the place for such a large event are subject to the approval of the mayor's office.
- The time and place for such a large event are subject to be approved by the office of the mayor.
- Subject to the approval of the mayor's office are the time and place for such a large event taking place.

VERBAL: Please select the word(s) that best complete the sentence below:

Favoring economy of expression in writing, the professor urged students toward a _____ rather than an _____ prose style.

- spare . . ornate
- terse . . opinionated
- personal . . academic
- baroque . . embellished
- repetitive . . intricate

Screen 8

You got 8/50 questions correct

Screen 9

Gender: Please specify your gender.

- ○ Male
- ○ Female

Age: Please specify your age.

Ethnicity/Race: Please specify your ethnicity/race.

- ○ White
- ○ Hispanic or Latino
- ○ Black or African American
- ○ Native American or American Indian
- ○ Asian / Pacific Islander
- ○ Other

Education: Please specify your highest level of education.

- ○ Some high school, no diploma
- ○ High school graduate, diploma or the equivalent (for example: GED)
- ○ Some college, no degree
- ○ Associate degree
- ○ Bachelor’s degree
- ○ Master’s degree
- ○ Professional degree
- ○ Doctorate degree

Screen 9 (cont.)

Marital status: Please specify your marital status.

- ○ Single, never married
- ○ Married or domestic partnership
- ○ Widowed
- ○ Divorced
- ○ Separated

Is English your native language?

- ○ Yes
- ○ No

How fluent are you in English?

1 (not at all fluent)	2 (somewhat not fluent)	3 (moderately fluent)	4 (somewhat fluent)	5 (very fluent)
○	○	○	○	○

Income: Please specify your household income.

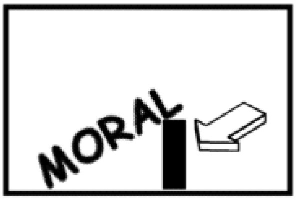
- ○ Less than $25,000
- ○ $25,000 to $34,999
- ○ $35,000 to $49,999
- ○ $50,000 to $74,999
- ○ $75,000 to $99,999
- ○ $100,000 to $149,999
- ○ $150,000 or more

Screen 10

[Screens 10-12 were displayed only in the **Delayed** treatment.

In the Immediate treatment, Screen 13 was displayed after Screen 9]

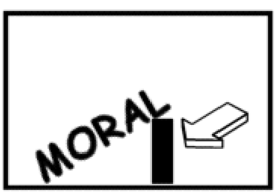
[if did NOT solve the 'moral support' puzzle in Stage 1]



In the puzzle task you did yesterday, you missed this puzzle! Do you want to see the solution?

- ○ Yes, I want to see the solution
- ○ No, I want to conclude

[if solved the 'moral support' puzzle in Stage 1]

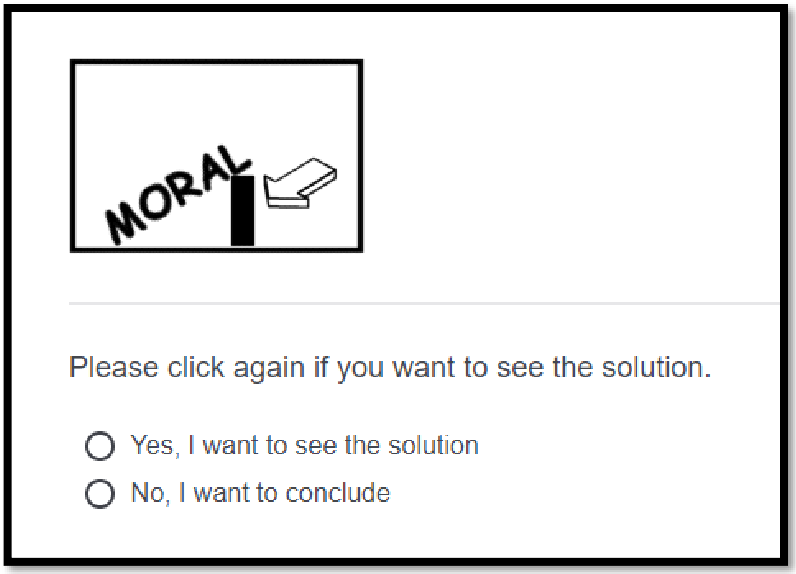


In the puzzle task you did yesterday, you got this puzzle correct! Do you still want to see the solution?

- ○ Yes, I want to see the solution
- ○ No, I want to conclude

Screen 11

[displayed only if selected ‘YES’ on Screen 10]



[repeated 4 times if selected ‘YES’]

Screen 12

[displayed only if selected ‘YES’ 4 times on Screen 11]

Screen 13

Thank you for participating in this study. You may be contacted back for additional HITs related to today's HIT. Click the arrow below to access your completion code

>>

Screen 14

Thank you for your participation!
Your code for completing this HIT is: R_2TADiq3UCqR9Jh0
IMPORTANT: Along with your Worker ID, this code is used to ensure you are paid for the work you did.
Please copy and paste the code into the HIT box.

8/50 16.0%

ART&LIT: Which Dickens character asked for more? 0/1

- The Artful Dodger
- ✕ Tiny Tim
- Miss Havisham
- Nicholas Nickleby
- Oliver Twist

[the correct solutions were displayed for all 50 trivia questions]

*** END OF STAGE 2 ***

***** END OF EXPERIMENT 1B *****

EXPERIMENT 2A

Screen 1

Please type in your MTURK WORKER ID:

What is your gender?

Female | Male | Other (please specify)

What is your age?

Screen 2

Welcome!

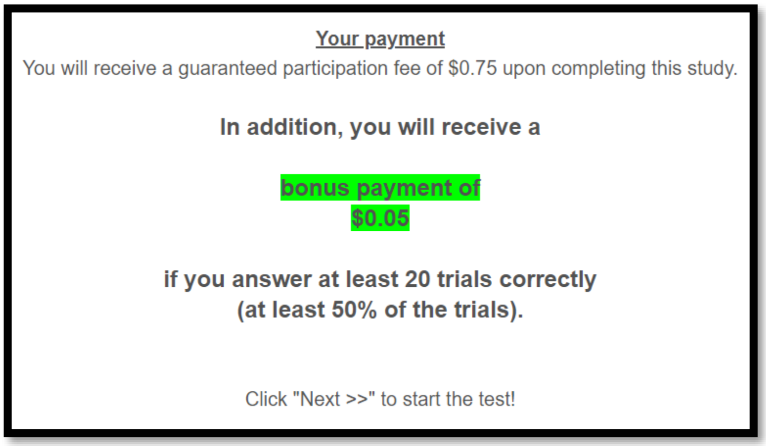
People have an intuitive ability to recognize emotions from facial expressions (especially the micro-expression of eyes) when interacting with others. This happens almost immediately and automatically. The purpose of the study is to examine people's ability to recognize emotions from facial expression.

In each trial, you will see a cropped portrait that shows the eyes of a person. The person depicted in the picture is displaying the facial expression associated with one of the six universal emotions: **happiness, sadness, anger, disgust, fear, or surprise**.

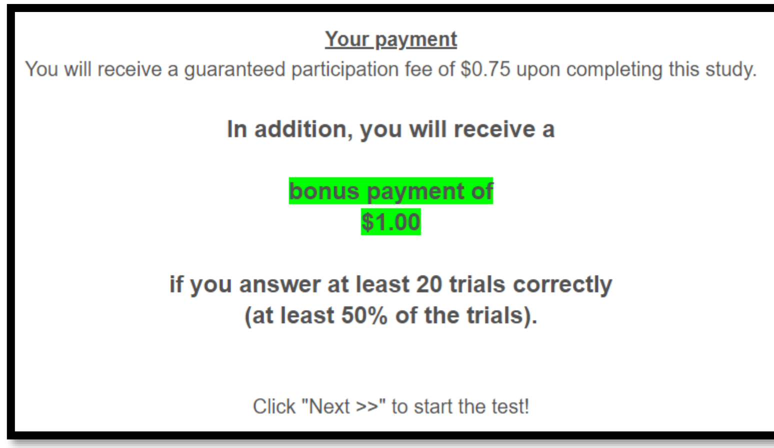
Your task will be to guess which emotion was the person is showing based only on his or her eyes. There will be **40** trials in this study.

Screen 3

Low Importance treatment

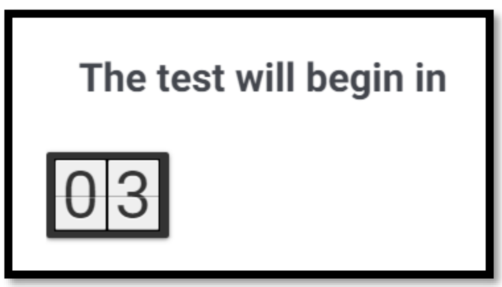


High Importance treatment

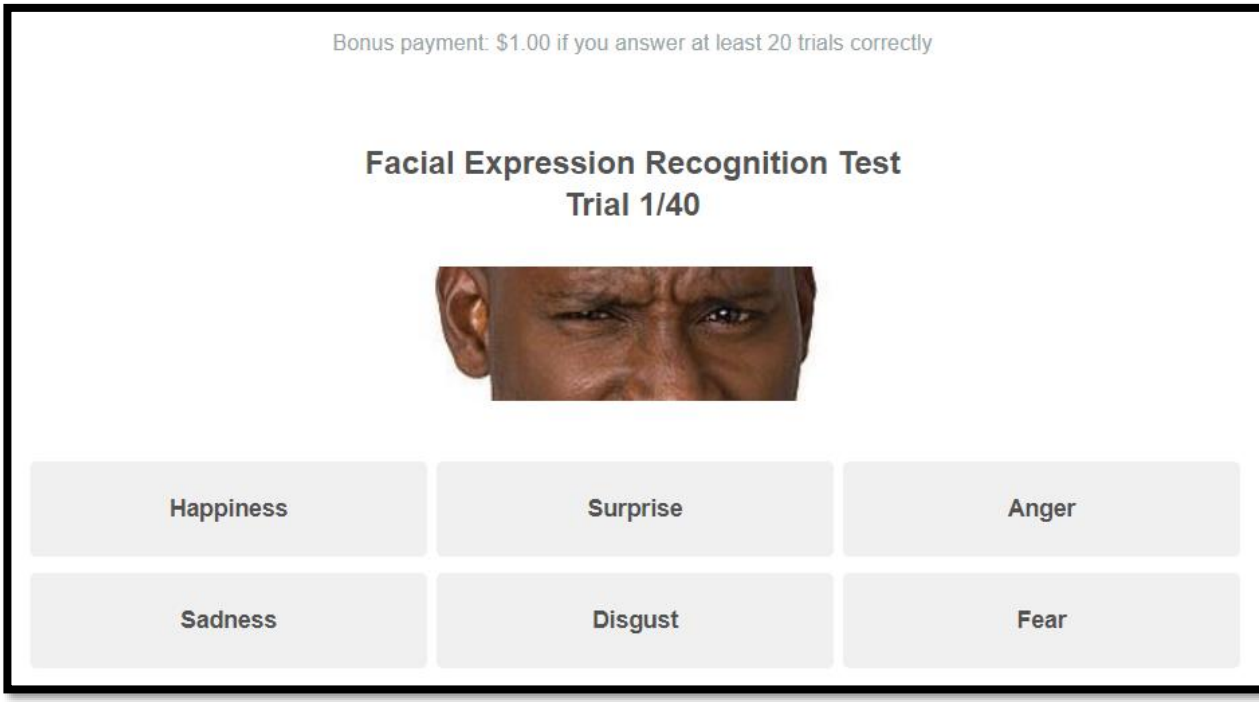


Screen 4

[auto-advances after 3 seconds]



Screen 5

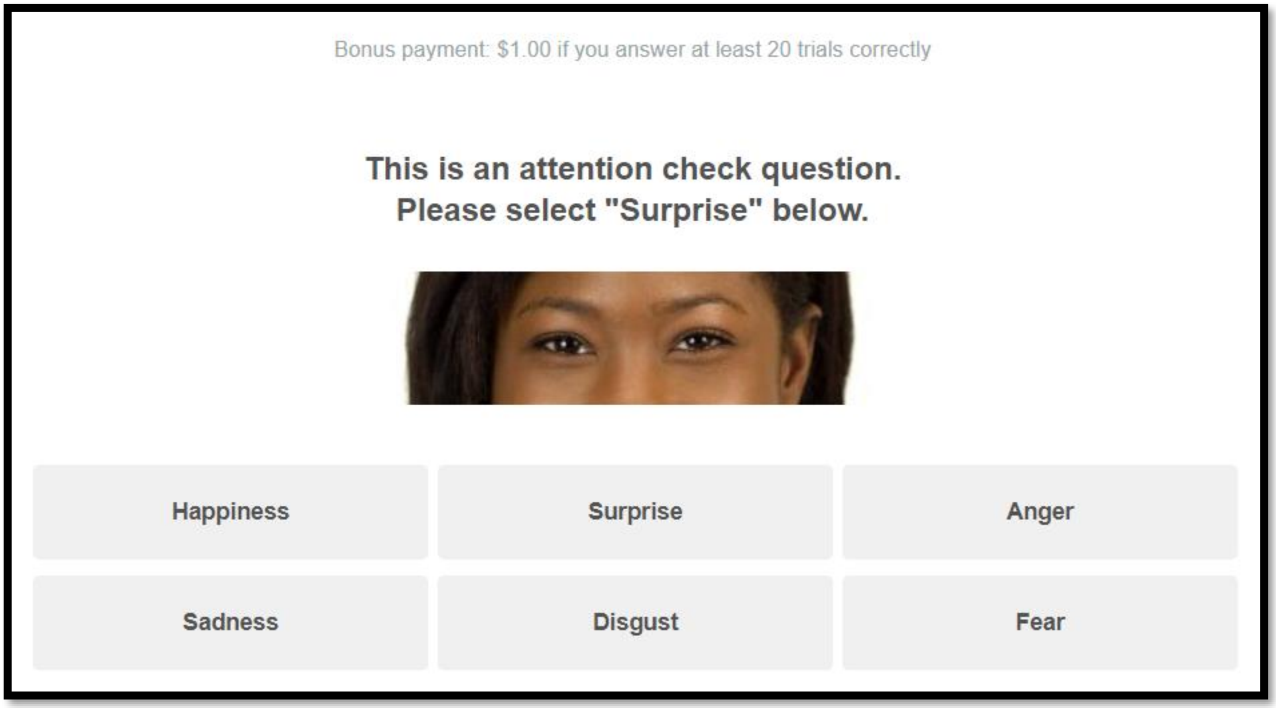


The screenshot above shows depicts the FER test in the High Importance treatment.

The FER test in the Low Importance treatment was identical, except for the reminder on the top of the screen, which displayed the following:

Bonus payment: $0.05 if you answer at least 20 trials correctly

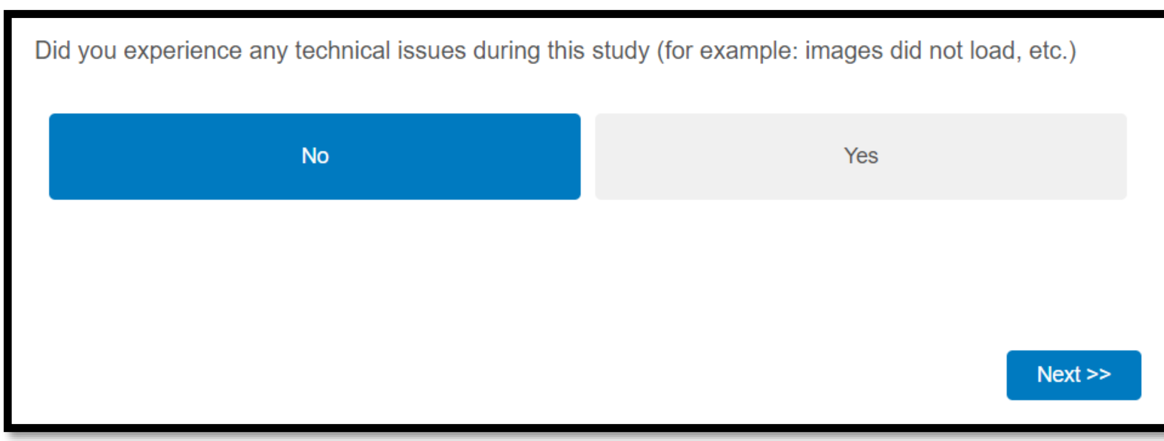
Screen 6


Bonus payment: $1.00 if you answer at least 20 trials correctly

This is an attention check question.
Please select "Surprise" below.

Happiness	Surprise	Anger
Sadness	Disgust	Fear

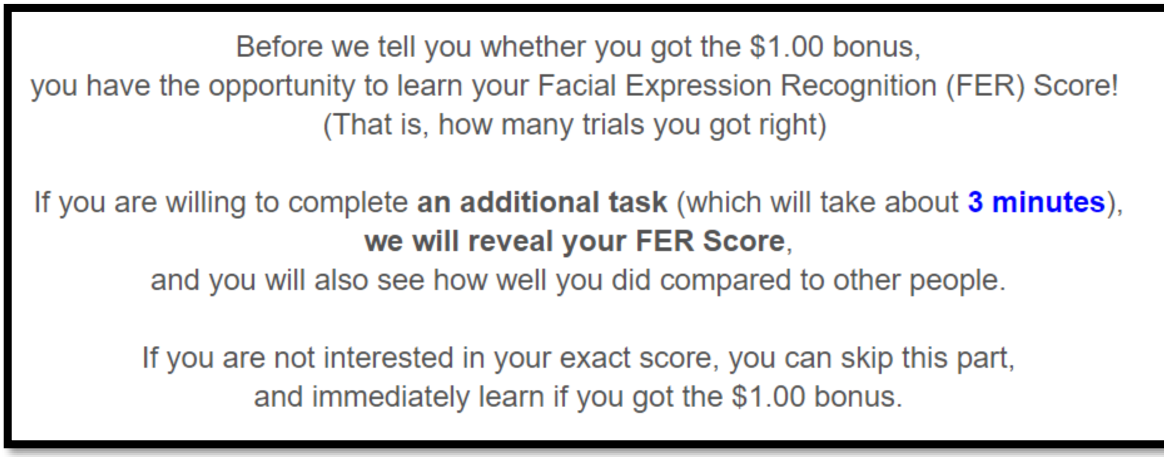
Screen 7


Did you experience any technical issues during this study (for example: images did not load, etc.)

No	Yes

Next >>

Screen 8



Before we tell you whether you got the $1.00 bonus,
you have the opportunity to learn your Facial Expression Recognition (FER) Score!
(That is, how many trials you got right)

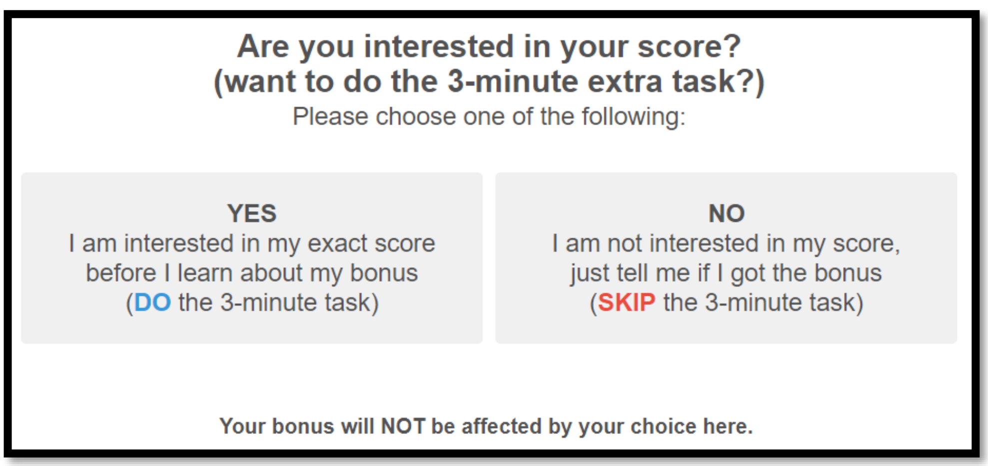
If you are willing to complete **an additional task** (which will take about **3 minutes**),
we will reveal your FER Score,
and you will also see how well you did compared to other people.

If you are not interested in your exact score, you can skip this part,
and immediately learn if you got the $1.00 bonus.

The screenshot above shows depicts the FER test in the High Importance treatment.

The FER test in the Low Importance treatment was identical, except for the bonus amount.

Screen 9



Are you interested in your score?
(want to do the 3-minute extra task?)
Please choose one of the following:

YES I am interested in my exact score before I learn about my bonus (**DO** the 3-minute task)	**NO** I am not interested in my score, just tell me if I got the bonus (**SKIP** the 3-minute task)

Your bonus will NOT be affected by your choice here.

Screen 10

Guess the age, 1/15

Please guess the age of the person below, as well as your confidence in your judgment, and then click "Next >>". After you complete all 15 guesses, your FER Score will be revealed.

< 20	20-29	30-39	40-49	49 <

How confident are you in your guess?

Not confident at all		Somewhat confident		Very confident
0	25	50	75	100

Screen 11

Before we tell you whether you got the $1.00 or not,
please answer the following questions:

How happy or unhappy would you feel if you got the $1.00 bonus?

Very unhappy | Neutral | Very happy
-100 -80 -60 -40 -20 0 20 40 60 80 100

How happy or unhappy would you feel if you did not get the $1.00 bonus?

Very unhappy | Neutral | Very happy
-100 -80 -60 -40 -20 0 20 40 60 80 100

How likely do you think it is that you got the $1.00 bonus?

I'm **CERTAIN that I did not get** the bonus | I'm completely **UNCERTAIN** | I'm **CERTAIN that I got** the bonus
0 10 20 30 40 50 60 70 80 90 100

Screen 12

Please answer the following question to ensure that you understood the instructions.

Did your decision to reveal your exact score affect your bonus payment?

Yes	No	Yes
I would have gotten a LOWER bonus if I revealed my exact score.	My decision whether to reveal my exact score DID NOT AFFECT my bonus payment in any way.	I would have gotten a HIGHER bonus if I revealed my exact score.

Screen 13

[Displayed only if the participant completed all 15 trials of the extra task (screen 10)]

Your Facial Expression Recognition Score:

5

That is, you got 5 out of 40 trials right.

You scored higher than 1.1% of other participants.

Screen 14

[if scored at least 50%]

Congratulations, you got at least 20 trials right!

Since you also passed the attention check,
You are eligible for the $0.05 bonus.

You will receive your validation code on the next screen.

Please let us know if you have any comments about this study:

[if scored below 50%]

Unfortunately, you got less than 20 trials right.

You did not get the bonus.

You will receive your validation code on the next screen.

Please let us know if you have any comments about this study:

Screen 15

Thank you for your participation!

Your code for completing this HIT is: R_z0eGDzu0TPWdUVH

IMPORTANT: Along with your Worker ID, this code is used to ensure you are paid for the work you did. Please copy and paste the code into the HIT box.

*** END OF EXPERIMENT 2A ***

EXPERIMENT 2B

STAGE 1: FER TEST

Screen 1

Please type in your MTURK WORKER ID:

What is your gender?

Female | Male | Other (please specify)

What is your age?

Screen 2

Welcome!

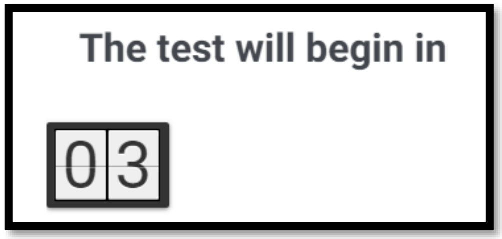
People have an intuitive ability to recognize emotions from facial expressions (especially the micro-expression of eyes) when interacting with others. This happens almost immediately and automatically. The purpose of the study is to examine people's ability to recognize emotions from facial expression.

In each trial, you will see a cropped portrait that shows the eyes of a person. The person depicted in the picture was instructed to mimic the facial expression associated with one of the six universal emotions:
happiness, sadness, anger, disgust, fear, or surprise.

Your task will be to guess which emotion was the person instructed to mimic, based on his or her portrait. There will be 40 trials in this study.

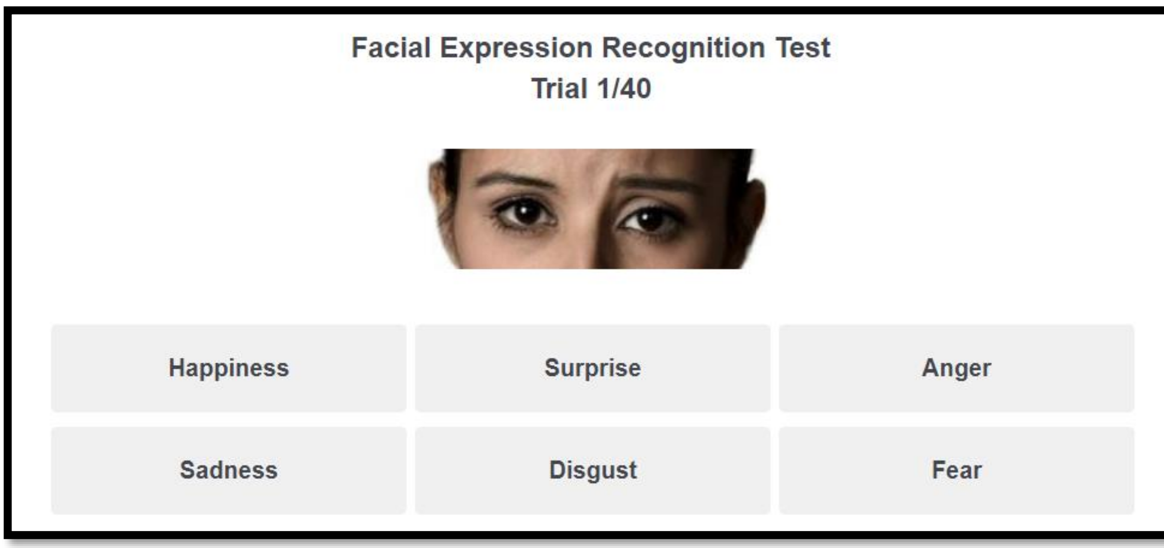
Screen 3

[auto-advances after 3 seconds]



Screen 4

[repeated 40 times]



Screen 5

[second question is displayed ONLY if ‘Yes’ is selected in the first question]

Did you experience any technical issues during this study (for example: images did not load, etc.)

No | Yes

Please describe the technical issue(s) you have experienced:

Screen 6

Please make a guess about your Facial Expression Recognition Score (between 0 and 100):

Screen 7

Thank you for your responses!

You will receive your validation code on the next screen.

Please let us know if you have any comments about this study:

Screen 8

Thank you for your participation!

Your code for completing this HIT is: R_ylMcnAQka0GQLBL

IMPORTANT: Along with your Worker ID, this code is used to ensure you are paid for the work you did. Please copy and paste the code into the HIT box.

*** END OF STAGE 1 ***

FOLLOW-UP EMAIL (UNANNOUNCED)

"Thank you for taking the Facial Expression Recognition Test on [DATE]. Now you have the opportunity to learn your Facial Expression Recognition Score! If you are willing to take 3 additional steps (which will take about 3 minutes in total), we will reveal your FER Score, and you will also see how well you did compared to other people. To reveal your score, please open the link and follow the instructions: [LINK]."

STAGE 2: FOLLOW-UP SURVEY (LINK PROVIDED IN FOLLOW-UP EMAIL)

Screen 1

You have the opportunity to learn your Facial Expression Recognition Score!

If you are willing to take **3 additional steps** (which will take about **3 minutes** in total), **we will reveal your FER Score**, and you will also see how well you did compared to other people.

STEP 1. Please choose one:

I am interested in my score

I am NOT interested in my score
(quit survey)

Screen 2

[ONLY if "I am interested" is selected, otherwise the survey is terminated]

STEP 2. Please type in your MTURK WORKER ID:

Screen 3

[repeated 15 times]

STEP 3. Guess the age! 1/15

Please guess the age of the person below, as well as your confidence in your judgment, and then click "Next >>". After you complete all 15 guesses, your FER Score will be revealed.

< 20	20-29	30-39	40-49	49 <

How confident are you in your guess?

Not confident at all		Somewhat confident		Very confident
0	25	50	75	100

Next >>

END SURVEY
Your FER Score will NOT be revealed
(skip this task; get validation code immediately)

(if "**END SURVEY**" is selected in any of the 15 trials, the survey is immediately terminated)

Screen 4

[ONLY if completed all 15 trials in Screen 3]

Your Facial Expression Recognition Score: 0%

The average FER Score is: 65.2%

Your scored higher than **0%** of people who have previously taken this test. This means that you were better than the **0%** of people at identifying emotions from facial micro-expressions.

*** END OF STAGE 2 ***

*** END OF EXPERIMENT 2B ***

EXPERIMENT 2C

Screen 1

Please type in your MTURK WORKER ID:

What is your gender?

Female | Male | Other (please specify)

What is your age?

Screen 2

Welcome!

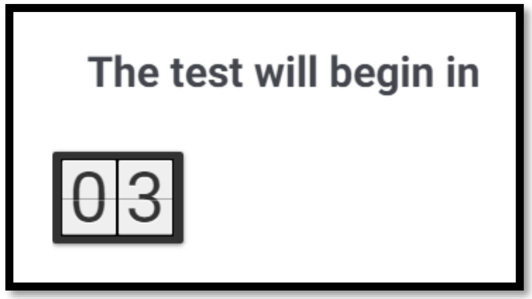
Many people have an intuitive, almost automatic, ability to recognize emotions from facial expressions (especially the micro-expression of eyes) when interacting with others. The purpose of the study is to examine people's ability to recognize emotions from facial expression.

In each trial, you will see a cropped portrait that shows the eyes of a person. The person depicted in the picture is exhibiting the facial expression associated with one of the six universal emotions: **happiness, sadness, anger, disgust, fear, or surprise**.

Your task will be to guess the person's emotion, based on the cropped portrait – that is, on his or her eyes. There will be 40 trials in this study.

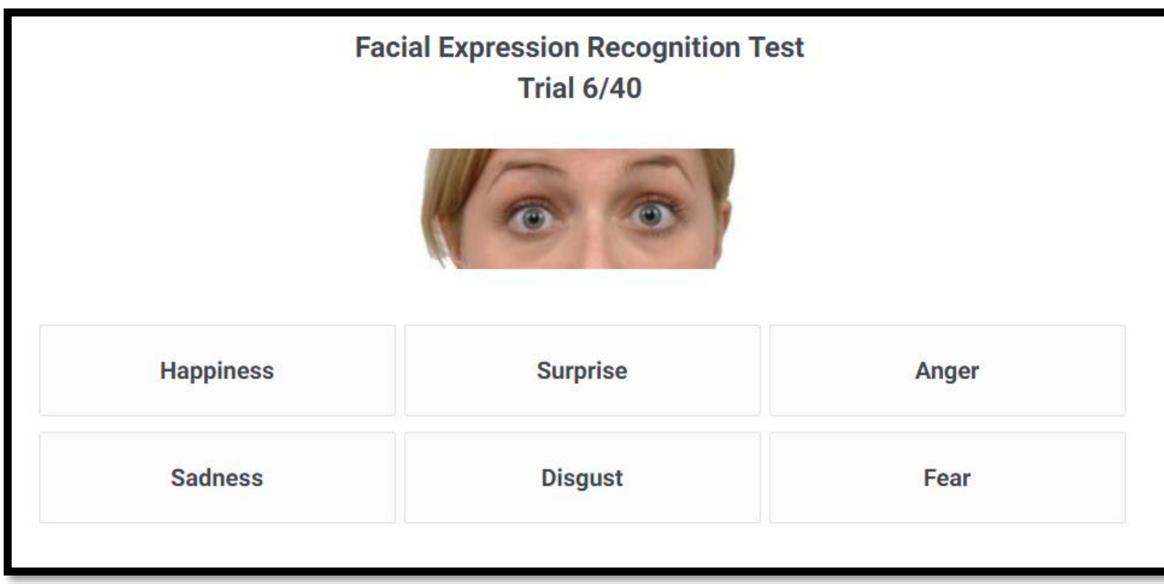
Screen 3

[auto-advances after 3 seconds]



Screen 4

[repeated 40 times; difficulty of trials varied by treatment]



Screen 5

[second question is displayed ONLY if ‘Yes’ is selected in the first question]

Did you experience any technical issues during this study (for example: images did not load, etc.)

No | Yes

Please describe the technical issue(s) you have experienced:

Screen 6

Thank you for taking the Facial Expression Recognition Test!

Before you go...

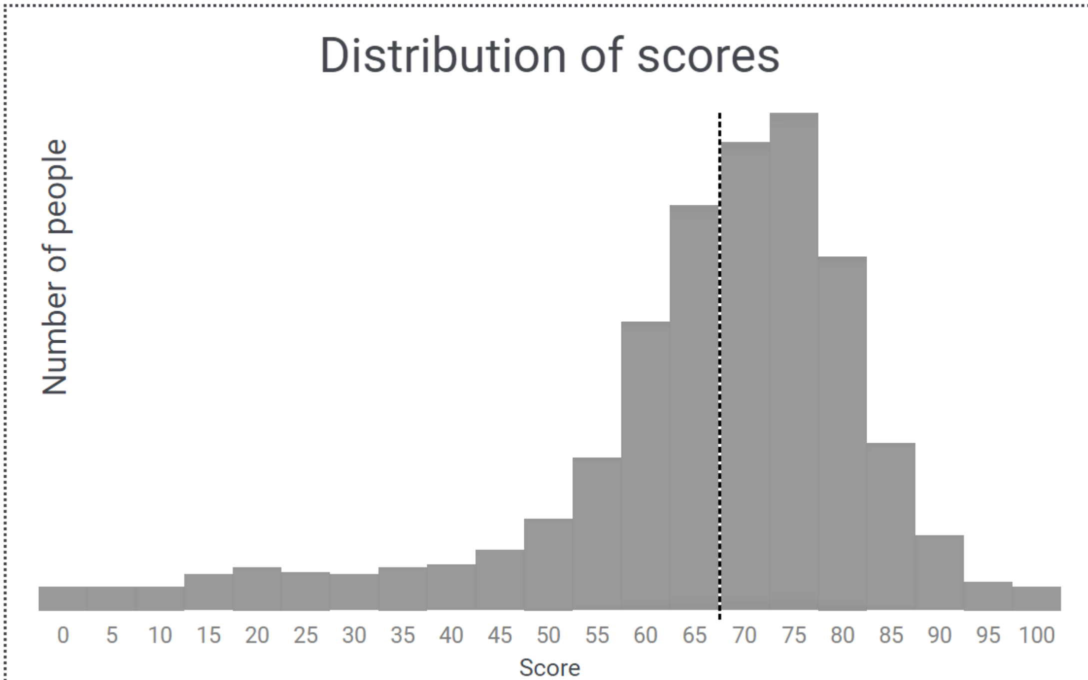
... You have the opportunity to learn your Facial Expression Recognition (FER) Score!

Screen 7

First, please make a guess about your FER score! (0 - 100)

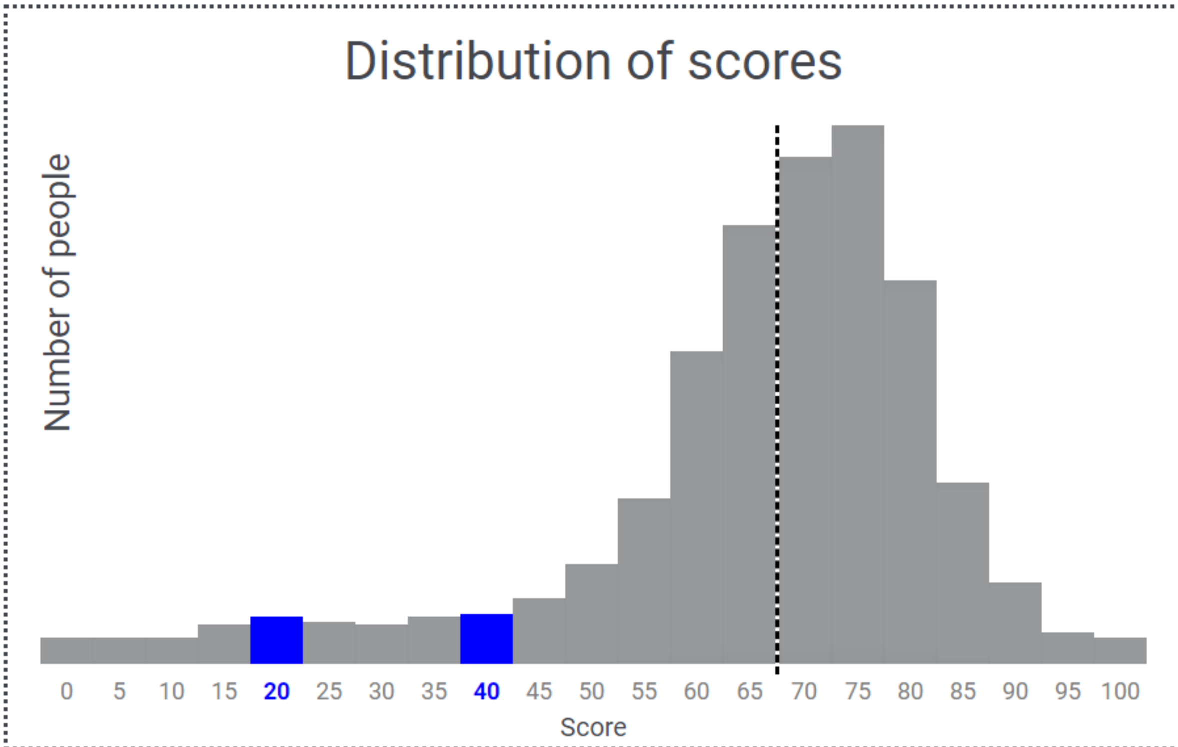
Screen 8

The chart below shows the distribution of FER Scores. Each bar indicates a group of people who scored 0%, 5%, 10%, etc., ... 100%. The higher the bars, the more people are in that group, that is, the more people obtained that score. The average score is **65%** (dashed line).



Screen 9

Based on your performance, we can already tell you that
YOU are in ONE of the TWO highlighted groups.



If you are willing to take **3 additional steps** (which will take about **3 minutes** in total), **we will reveal which group YOU are in**.

STEP 1. Please choose one:

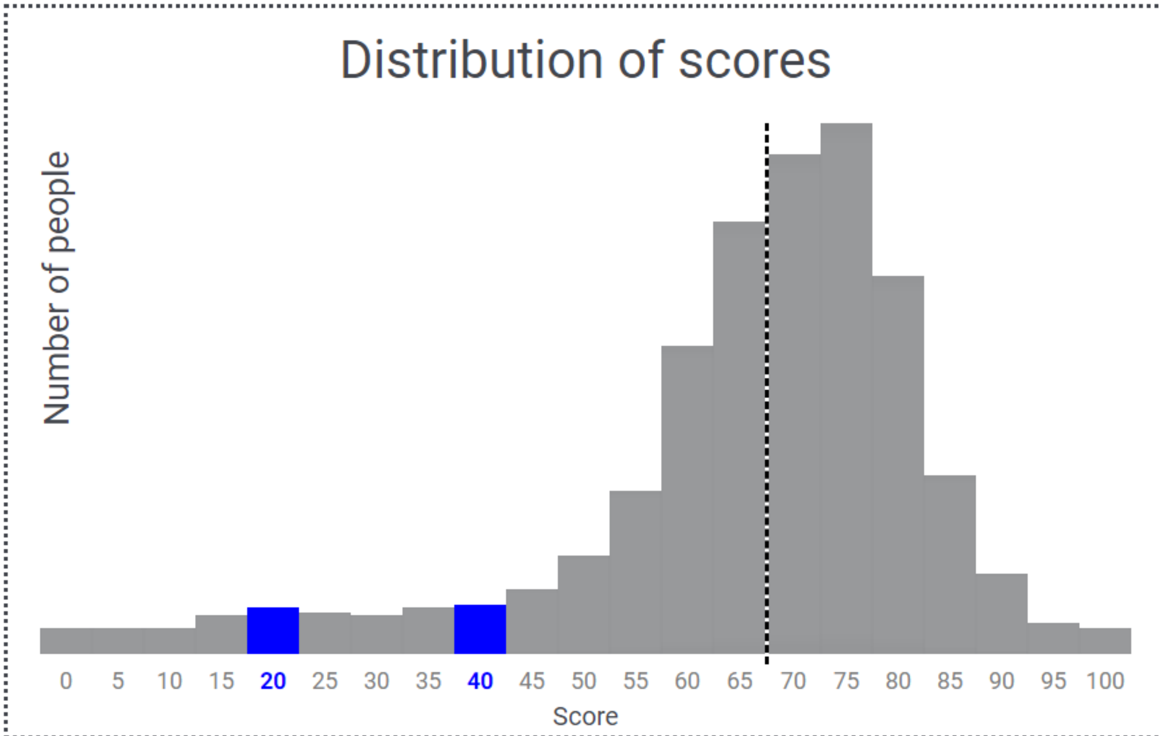
I am interested in my score	I am NOT interested in my score (skip to end of survey; get validation code immediately)

(if "I am NOT interested" is selected, skip Screens 10-12, jump to Screen 13)

Screen 10

STEP 2. What do you think: which of the following is your score?

20%	40%



Screen 11

[repeated 10 times]

STEP 3. Guess the age! 1/10

Please guess the age of the person below, as well as your confidence in your judgment, and then click "Next >>". After you complete all 10 guesses, your FER Score will be revealed.

< 20	20-29	30-39	40-49	49 <

How confident are you in your guess?

Not confident at all		Somewhat confident		Very confident
0	25	50	75	100

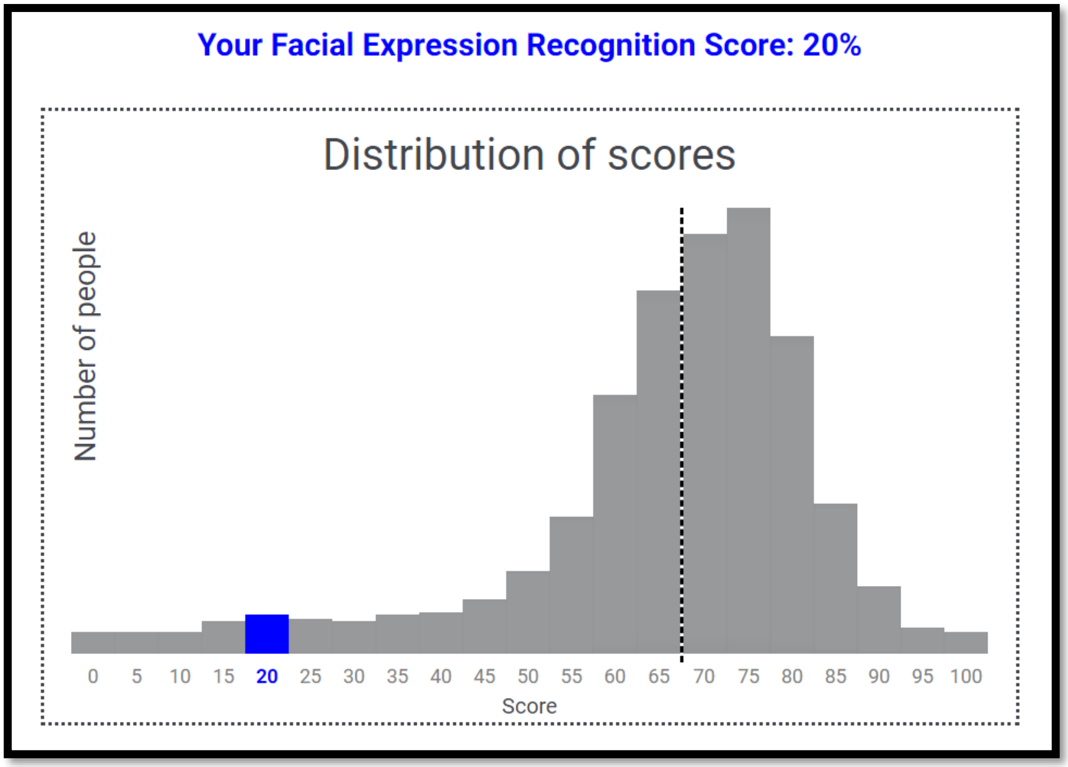
Next >>

END SURVEY
Your FER score will NOT be revealed
(skip this task; get validation code immediately)

(If "END SURVEY" is selected in any of the 10 trials, jump immediately to Screen 13)

Screen 12

[displayed ONLY if completed all 10 trials in Screen 11]



Screen 13

Please let us know if you have any comments about this study:

Screen 14

Thank you for your participation!

Your code for completing this HIT is: R_3O8uBPLdzDJ7ljl

IMPORTANT: Along with your Worker ID, this code is used to ensure you are paid for the work you did. Please copy and paste the code into the HIT box.

*** END OF EXPERIMENT 2C ***

The Facial Expression Recognition Test used in Experiments 2A, 2B, & 2C

We created the Facial Expression Recognition (FER) test using four different sources for stimuli: the Chicago face database (CFD, Ma, Correll, & Wittenbrink, 2015), the Radboud Faces Database (RaFD, Langner et al., 2010), the Extended Cohn-Kanade Dataset (CK+, Lucey et al., 2010) and images found by using Google search. The final database consisted of 73 high-resolution color photos depicting people of various ethnicity, age, and gender. Each participant was presented with a randomly selected subset of 40 photos from the database of 73 images. To ensure that the people were experiencing particular emotions, and that audiences were able to perceive these, the full photos were validated by the original authors (36 photos from CFD, 16 from RaFD, and 1 from CK+), while we conducted a pretest to validate the 20 photos found via Google search.

To guarantee that the photos coming from different sources were presented in a standardized format, we adjusted their size, color, and contrast. The experimental stimuli used in the study were 80 pixels high cropped photos showing only the area around the eyes (see next page). In the FER test, participants were shown cropped portraits of people and they had to guess which of six emotions (happiness, sadness, anger, disgust, fear, surprise) the person in the photo was instructed to mimic. Participants guessed emotions in 40 photos, and their score on the test was the percentage of correct guesses. The accuracy on individual photos (the proportion of people who guessed the emotion depicted in the photo correctly) ranged from 10.2% to 97.1%.

Photos were presented one by one, and participants could take as much time to make a guess as they wished (there was no time limit). However, after they submitted their guess for a photo, they could not go back or revise previous guesses. In the FER test used in Experiments 2A and 2B each participant was presented with 40 photos which were randomly selected from the database of 73 photos. In Experiment 2C we manipulated the overall difficulty of the FER test across treatments by oversampling easy or hard photos. Half of the participants were presented photos most of which were relatively easy to guess (*easy* treatment), while the other half had photos most of which were hard to guess (*hard* treatment).

Photos used in the FER test (uncropped)

Source: Chicago Face Database (36 photos)

Source: Radboud Faces Database (16 photos)

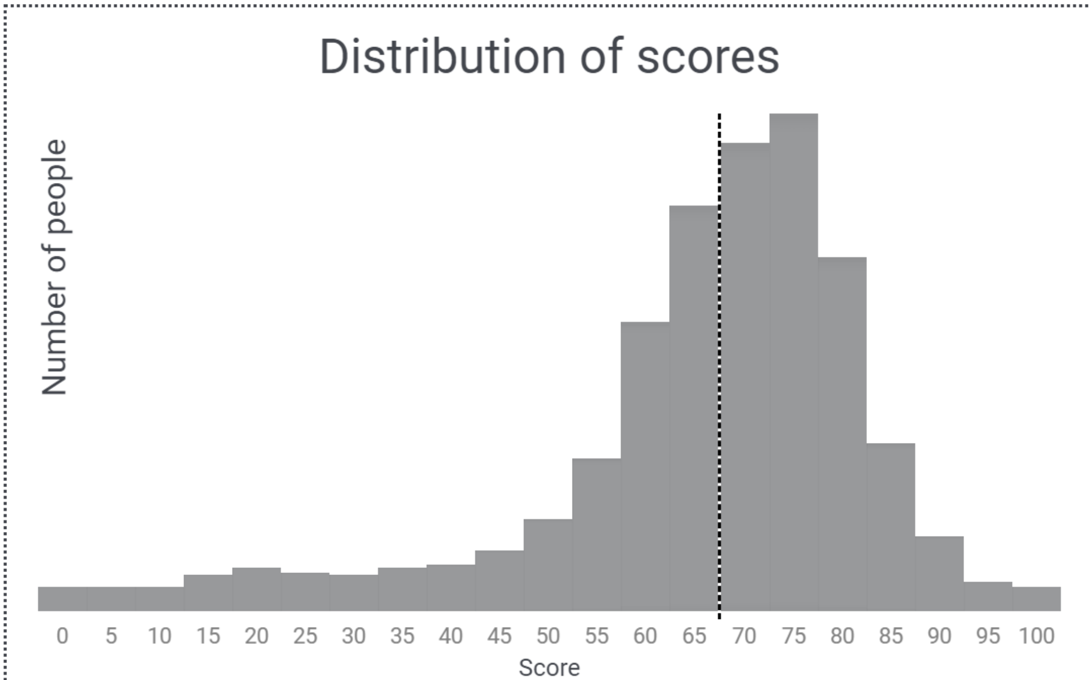
Source: Google (20 photos)

Source: Extended Cohn-Kanade Dataset (1 photo)

Combined database: stimuli used in experiments (cropped version of the full photos)

Experimental stimulus showing the distribution of FER scores, Experiment 2C.

The chart below shows the distribution of FER Scores. Each bar indicates a group of people who scored 0%, 5%, 10%, etc., ... 100%. The higher the bars, the more people are in that group, that is, the more people obtained that score. The average score is **65%** (dashed line).



Next >>

Figure B1. Experimental stimulus used in Experiment 2C, showing the distribution of FER scores obtained by previous participants.

Appendix C: A priori power analyses

Experiment 1A. We conducted an a priori power calculation in G*Power 3.1.9.2 (Faul et al., 2009) to determine the required minimum sample size. To be able to detect a significant effect at the conventional significance level ($p < .05$), with a moderate effect size (Cohen's $d = 0.30$) in an independent samples t-test between the two treatments, at a power of $1 - \beta = .95$, we needed at least 290 observations per treatment. Since our analyses are limited to people who fail to answer the target puzzle ("moral support"), we had to recruit significantly more people than 290 per treatment. Based on our pre-test results we expected that at least 30% of people would be able to solve the target puzzle, thus we needed at least 414 participants per treatment to have 290 observations per treatment. Based on this power calculation, we aimed to have 420 participants per treatment in our final sample (840 total).

Experiment 1B. We conducted an a priori power calculation in G*Power 3.1.9.2 (Faul et al., 2009) to determine the required minimum sample size. To be able to detect a significant effect at the conventional significance level ($p < .05$), with a large effect size (Cohen's $d \geq 0.80$)[14] in an independent samples t-test between the two treatments, at a power of $1 - \beta = .95$, we needed at least 42 observations per treatment. Since our analyses are limited to people who fail to answer the target puzzle ("moral support") *and* return to the second part of the experiment, we had to recruit significantly more people than 42 per treatment. Based on the results of Experiment 1A, we expected that about 40% of people would be able to solve the target puzzle, thus we needed at least 70 participants per treatment who completed both parts of the experiment. We also assumed that there would be a substantial proportion of participants (about 30%) who would not return to the second part of the experiment, therefore we aimed to have 100 participants per treatment completing the first part of the experiment (200 total).

Experiment 2A. We conducted an a priori power calculation in G*Power 3.1.9.2 (Faul et al., 2009) to determine the required minimum sample size. To be able to detect a significant ($p < .05$) 10% difference (Cohen's $w = 0.20$) in a Chi-square goodness-of-fit test between any two treatments, at a power of $1 - \beta = .95$, we needed at least 163 observations per treatment. Based on this power calculation, we aimed to have 150 observations per treatment in our final sample (450 total).

Experiment 2B. We conducted an a priori power calculation in G*Power 3.1.9.2 (Faul et al., 2009) to determine the required minimum sample size. To be able to detect a significant ($p < .05$) 10% difference (Cohen's $w = 0.20$) in a Chi-square goodness-of-fit test between the two treatments, at a power of $1 - \beta = .95$, we needed at least 163 observations per treatment. Based on this power calculation, we aimed to have 200 observations per treatment in our final sample (400 total).

Experiment 2C. We conducted an a priori power calculation in G*Power 3.1.9.2 (Faul et al., 2009) to determine the required minimum sample size. To be able to detect a significant ($p < .05$) 10% difference (Cohen's $w = 0.20$) in a Chi-square goodness-of-fit test between the two treatments, at a power of $1 - \beta = .99$, we needed at least 230 observations per treatment. Based on this power calculation, we aimed to have 250 observations per treatment in our final sample (500 total).

[14]This expected effect size was a conservative estimate based on the results of Experiment 1A.

Appendix D: Supplemental Analyses

Experiment 1A

Behavior of participants who solved the "moral support" puzzle, Experiment 1A. Out of the 363 participants who solved the "moral support" puzzle, 254 (70.0%) immediately declined revealing the solution (did not click the reveal button even once), and the average number of clicks was only $M = 0.90$ ($SD = 1.72$). Among these people—who managed to solve the last puzzle—we did not observe a significant difference in the proportion who declined revealing the solution between the *Low Importance* treatment, $M = 72.9\%$, and the *High Importance* treatment, $M = 67.0\%$, $\chi^2(1, N = 363) = 1.234, p = .267$. Similarly, we did not observe any significant difference in the average click count between the *Low Importance*, $M = 0.84$, and the *High Importance* treatments, $M = 0.96$, $t(361) = 0.673, p = .502$.

OLS regression analysis and demographic robustness checks, Experiment 1A.

Table D1. OLS regression results, Experiment 1A

	Dependent variable:					
	Number of clicks		Started clicking		Clicked ten times	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: High Importance	1.339*** (0.278)	1.279*** (0.344)	0.092*** (0.023)	0.127*** (0.028)	0.112** (0.036)	0.092* (0.046)
Total score		0.595*** (0.138)		0.030** (0.011)		0.031′ (0.018)
Time: 1st practice puzzle		−0.260 (0.205)		0.011 (0.017)		−0.039 (0.027)
Time: 2nd practice puzzle		0.310′ (0.178)		−0.003 (0.015)		0.051* (0.024)
Time: 1st bonus puzzle		0.083 (0.138)		0.014 (0.011)		0.020 (0.018)
Time: 2nd bonus puzzle		0.074 (0.151)		0.035** (0.012)		−0.003 (0.020)
Time: 3rd bonus puzzle (“moral support”)		0.500** (0.186)		0.023 (0.015)		0.058* (0.025)
Sex: Female		−0.125 (0.274)		0.022 (0.023)		−0.029 (0.037)
Constant	4.339*** (0.196)	2.730*** (0.384)	0.887*** (0.016)	0.748*** (0.032)	0.142*** (0.026)	0.042 (0.051)
Observations	475	472	475	472	475	472
R^2	0.047	0.120	0.034	0.095	0.020	0.058
Adjusted R^2	0.045	0.105	0.031	0.080	0.018	0.041

Note: $'p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Histograms of click counts, Experiment 1A.

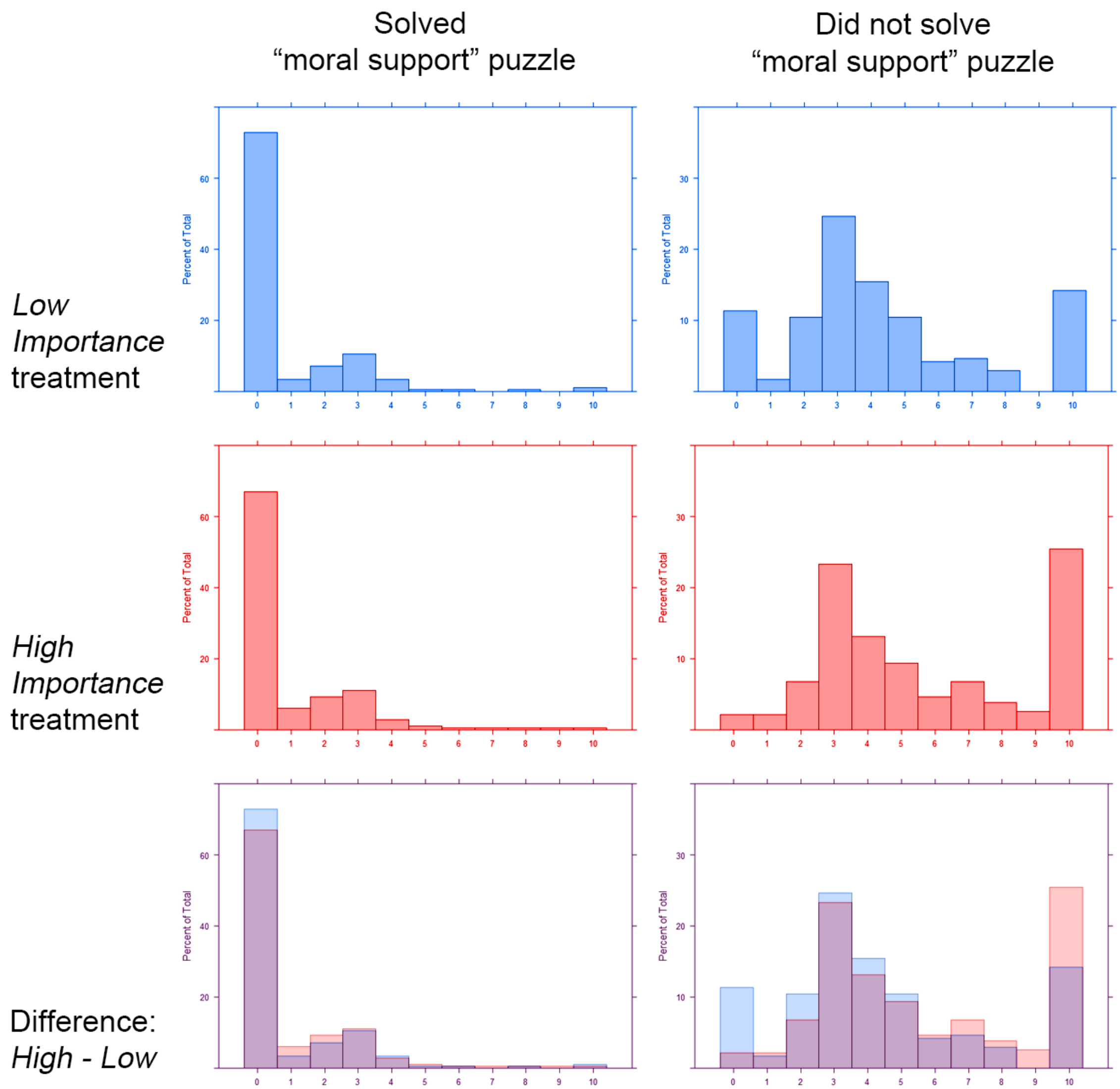


Figure D1. Histograms of total click counts, grouped by experimental treatment and whether participants could solve the “moral support” puzzle, Experiment 1A. Click counts (0–10) are depicted along the X-axes, while relative frequencies (%) are depicted along the Y-axes.

Experiment 1B

Behavior of participants who solved the "moral support" puzzle, Experiment 1B. Out of the 49 participants who solved the "moral support" puzzle, 22 (44.9%) immediately skipped revealing the solution, and the average number of clicks was $M = 1.73$ ($SD = 1.85$). Among these people—who managed to solve the last puzzle—we did not observe any significant difference in the average click counts between the *Immediate*, $M = 2.09$, and the *Delayed* treatments, $M = 1.44$, $t(44) = 1.221, p = .229$.

OLS regression analysis and demographic robustness checks, Experiment 1B.

Table D2. OLS regression results, Experiment 1B

	Dependent variable:					
	Number of clicks		Started clicking		Clicked 5 times	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Immediate	1.046***	0.949***	0.114*	0.083′	0.586***	0.579***
	(0.279)	(0.272)	(0.050)	(0.048)	(0.071)	(0.071)
Total score		0.622**		0.099**		0.109′
		(0.213)		(0.037)		(0.055)
Total time (min)		0.166′		0.003		0.046*
		(0.087)		(0.015)		(0.023)
Sex: Female		0.107		0.106*		−0.051
		(0.280)		(0.049)		(0.073)
Age (years)		0.001		0.003		0.0003
		(0.011)		(0.002)		(0.003)
Constant	3.226***	1.889**	0.868***	0.558***	0.377***	0.140
	(0.199)	(0.564)	(0.035)	(0.099)	(0.051)	(0.147)
Observations	108	108	108	108	108	108
R^2	0.117	0.216	0.047	0.185	0.392	0.434
Adjusted R^2	0.109	0.178	0.038	0.145	0.386	0.406

Note: $'p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Histograms of click counts, Experiment 1B.

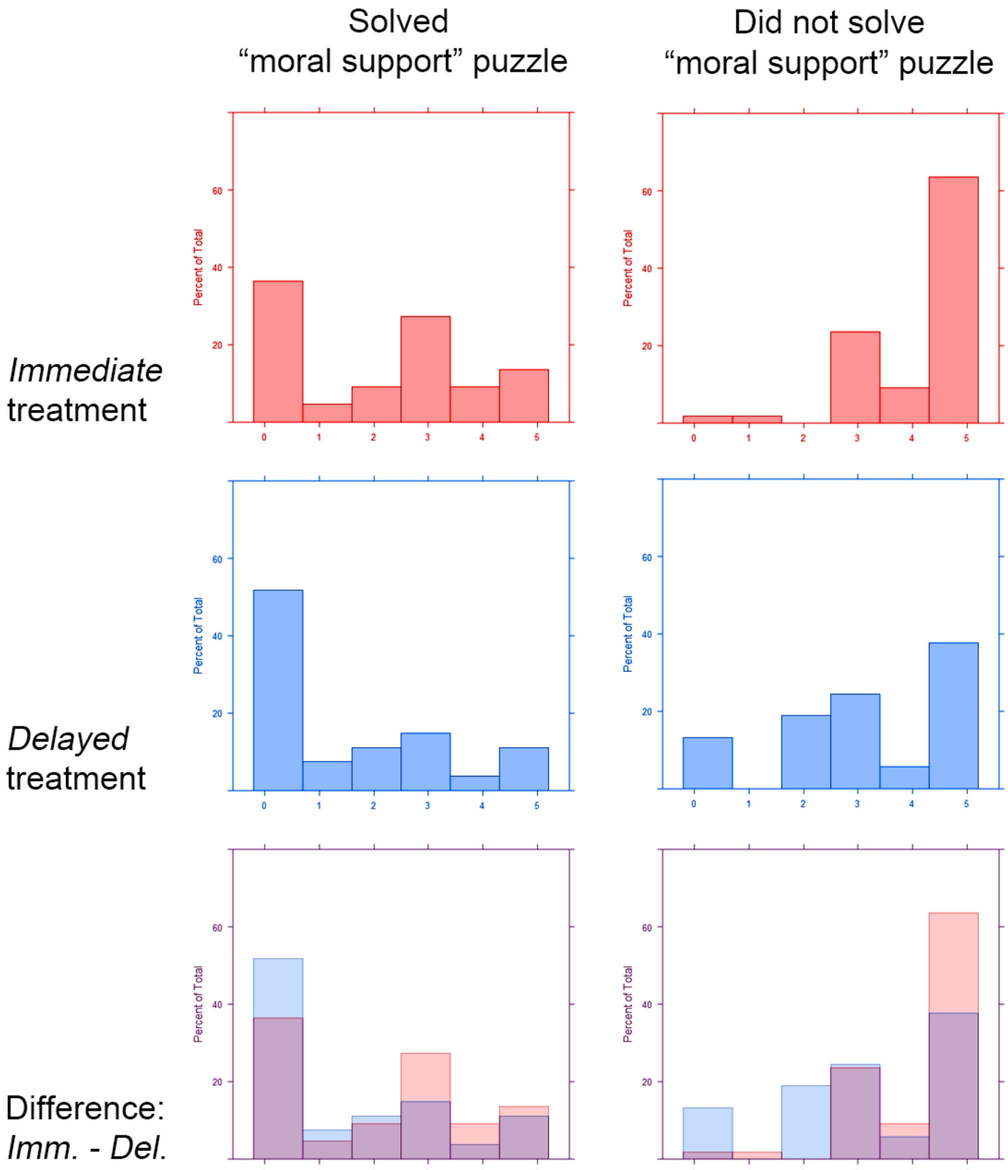


Figure D2. Histograms of total click counts, grouped by experimental treatment and whether participants could solve the “moral support” puzzle, Experiment 1B. Click counts (0–5) are depicted along the X-axes, while relative frequencies (%) are depicted along the Y-axes.

Testing for potential selection effects in Experiment 1B. To test whether people who completed the second stage of the experiment differed in their behavior from those who dropped out after the first stage, we compared the willingness to reveal the solution between these groups among participants who had been assigned to the *immediate* treatment. We could not investigate the behavior of the participants assigned to the *delayed* treatment, since by definition, we did not observe the behavior of those who dropped out after the first stage.

There were 98 unique participants who completed the first stage in the *immediate* treatment. Out of these people, 77 (79%) returned and completed the second stage, while 21 (21%) did not.

When we compare the behavior of these groups, we do not find any significant differences, regardless of whether participants did or did not solve the "moral support" puzzle (see Figure D3).

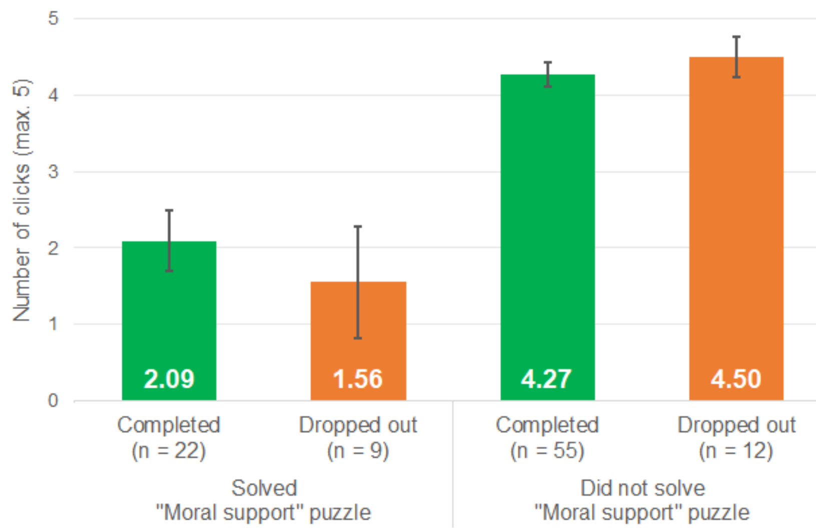


Figure D3. Mean number of clicks to reveal the solution to the final puzzle ("moral support") in the *immediate* treatment in Experiment 2A, grouped by whether participants could solve this puzzle, and whether participants completed the second stage of the experiment. Error bars represent $\pm 1SE$.

Among those who solved this puzzle, people who completed both stages clicked on average 2.09 times, while people who dropped out clicked 1.56 times, $t(13) = 0.644$, $p = .531$, Cohen's $d = 0.27$, 95% CI $[-1.26, 2.33]$. Similarly, there was no significant difference in the average number of clicks among people who did not solve the "moral support" puzzle, between those who completed both stages, $M = 4.27$, and those who dropped out, $M = 4.50$, $t(19) = 0.752$, $p = .461$, Cohen's $d = 0.21$, 95% CI $[-0.86, 0.40]$.

Thus, although this is admittedly a small sample, the above results do not provide any evidence for a selection confound: Whether participants decided to return to the second stage or not, did not seem to have affected their willingness to reveal the solution to the last puzzle.

Experiment 2A

OLS regression analysis and demographic robustness checks, Experiment 2A.

Table D3. OLS regression results, Experiment 2A

	Dependent variable:					
	STARTED task			COMPLETED task		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: High bonus	0.131**	0.050	0.001	0.114*	0.038	0.005
	(0.047)	(0.052)	(0.059)	(0.046)	(0.051)	(0.058)
Subjective importance: $\mathrm{SD}(U)$		0.003***	0.003**		0.003**	0.003**
		(0.001)	(0.001)		(0.001)	(0.001)
Fixed payment: High ($1.70)			$-0.095'$			-0.067
			(0.055)			(0.054)
Actual score			0.006			0.006
			(0.005)			(0.005)
Sex: Female			-0.010			0.012
			(0.044)			(0.044)
Age (years)			-0.0001			-0.0001
			(0.0002)			(0.0002)
Constant	0.336***	0.265***	0.170	0.309***	0.243***	0.137
	(0.028)	(0.034)	(0.129)	(0.027)	(0.034)	(0.127)
Observations	470	470	470	470	470	470
R^2	0.016	0.040	0.049	0.013	0.035	0.041
Adjusted R^2	0.014	0.036	0.037	0.011	0.030	0.028

Note: $'p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Experiment 2B

OLS regression analysis and demographic robustness checks, Experiment 2B.

Table D4. OLS regression results, Experiment 2B

	Dependent variable: started the real effort task to reveal score within ... after receiving the email									
	0–15 min		0–30 min		0–60 min		0-120 min		48 hours (ever)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment:	0.075^{*}	0.069^{*}	0.090^{*}	0.080^{*}	0.106^{*}	0.095^{*}	0.116^{*}	0.104^{*}	$0.085^{\prime}$	0.062
Immediate	(0.033)	(0.033)	(0.040)	(0.040)	(0.043)	(0.043)	(0.046)	(0.046)	(0.049)	(0.048)
Total score		0.003^{*}		0.004^{*}		0.003^{*}		0.003		0.005^{**}
		(0.001)		(0.001)		(0.002)		(0.002)		(0.002)
Sex: Female		−0.020		0.006		−0.003		0.013		0.036
		(0.034)		(0.040)		(0.043)		(0.046)		(0.048)
Age (years)		0.0004		0.001		$0.004^{\prime}$		0.005^{*}		0.009^{***}
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)
Constant	0.090^{***}	−0.107	0.151^{***}	−0.132	0.191^{***}	−0.139	0.251^{***}	−0.090	0.372^{***}	-0.272^{*}
	(0.024)	(0.090)	(0.028)	(0.106)	(0.030)	(0.115)	(0.033)	(0.123)	(0.035)	(0.128)
Observations	398	398	398	398	398	398	398	398	398	398
R^2	0.013	0.028	0.013	0.033	0.015	0.038	0.016	0.039	0.008	0.083
Adjusted R^2	0.010	0.018	0.010	0.023	0.013	0.028	0.013	0.029	0.005	0.074

Note: $^{\prime}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Robustness checks, Experiment 2B.

Threshold: 15 minutes. 16.6% started the extra task within 15 minutes after receiving the email in the *Immediate* treatment, and 9.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 4.408, p = .035$. By contrast, 29.2% started the extra task *at least* 15 minutes after receiving the email in the *Immediate*, while 28.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 0.012, p = .912$.

Threshold: 30 minutes. 24.1% started the extra task within 30 minutes after receiving the email in the *Immediate* treatment, and 15.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 4.608, p = .032$. By contrast, 21.6% started the extra task *at least* 30 minutes after receiving the email in the *Immediate*, while 22.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 0.000, p = 1.000$.

Threshold: 1 hour (REPORTED IN MAIN TEXT). 29.7% started the extra task within 1 hour after receiving the email in the *Immediate* treatment, and 19.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 5.453, p = .020$. By contrast, 16.1% started the extra task *at least* 1 hour after receiving the email in the *Immediate*, while 18.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 0.160, p = .690$.

Threshold: 2 hours. 36.7% started the extra task within 2 hours after receiving the email in the *Immediate* treatment, and 25.1% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 5.695, p = .017$. By contrast, 9.1% started the extra task *at least* 2 hours after receiving the email in the *Immediate*, while 12.0% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 0.665, p = .415$.

Threshold: 4 hours. 40.7% started the extra task within 4 hours after receiving the email in the *Immediate* treatment, and 31.7% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 3.145, p = .076$. By contrast, 5.0% started the extra task *at least* 4 hours after receiving the email in the *Immediate*, while 5.5% did so in the *Delayed* treatment, $\chi^2(1, N = 398) = 0.000, p = 1.000$.

Experiment 2C

OLS regression analysis and demographic robustness checks, Experiment 2C.

Table D5. OLS regression results, Experiment 2C

	Dependent variable:					
	STARTED effort task			COMPLETED effort task		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment: Easy	0.134**	0.014	0.006	0.149***	−0.002	−0.010
	(0.044)	(0.072)	(0.071)	(0.044)	(0.072)	(0.071)
Expected score (mean of two scores)		0.003*	0.003*		0.004**	0.004*
		(0.002)	(0.002)		(0.002)	(0.002)
Time spent on FER test (min)			0.013			0.009
			(0.019)			(0.019)
Sex: Female			0.158***			0.151***
			(0.044)			(0.044)
Age (years)			0.005*			0.005*
			(0.002)			(0.002)
Constant	0.500***	0.337***	0.051	0.437***	0.230**	−0.026
	(0.031)	(0.084)	(0.118)	(0.031)	(0.084)	(0.119)
Observations	498	498	498	498	498	498
R^2	0.018	0.027	0.069	0.022	0.036	0.072
Adjusted R^2	0.016	0.023	0.059	0.020	0.032	0.062

Note: $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Appendix E

Application: Genetic Testing

Here we provide an illustration of how our model can be applied in a concrete setting to generate new insights. In particular, we use it to provide a new perspective on Oster et al.'s (2013) findings about the propensity for genetic testing for Huntington's Disease (HD). Oster et al. applied Brunnermeier and Parker's (2005) model to account for their findings, based on the premise that people avoid getting tested so they can remain optimistic. We illustrate how our model provides an alternative account of test-avoidance based on attention management rather than optimism maintenance.

We begin by describing an individual's cognitive state before getting tested. The activated question that we will focus on is Q, "Do I have the HD gene?" The answer to this question has implications for a wide range of material outcomes, but we might summarize the relevant material outcomes by lifespan T and consumption stream $C(t)$, i.e., we make the gross oversimplification $X = \{T, C(t)\}$. Of course, an individual's lifespan and future consumption are both uncertain (and may even depend in part on future choices, such as when to seek medical attention or when to retire), so the individual has a prior belief π about the probability of having the HD gene along with various possible lifespans and consumption streams. (The probability of having the gene is $p = \pi_Q(\text{yes})$ and the probability of not having the gene is $1-p = \pi_Q(\text{no})$, and the probability distribution for lifespan T and consumption stream $C(t)$ is dependent on that answer.) But, while the answer to the activated question Q and the material outcomes X are both uncertain, we have assumed that the individual is aware of the question about the HD gene, whereas she may not be thinking specifically about her lifespan or future consumption. The uncertainty about whether she has the HD gene presents an information gap, and she pays attention to it. Factors that affect the amount of attention weight w on this question (i.e., its salience, its importance, and surprise following new information) then affect whether (and at what cost) genetic testing will be pursued.

Essentially, getting genetic testing changes the individual's cognitive state. With probability p the new cognitive state is defined by belief π^{yes} (in which the probability of having the gene is 1 and the probability distribution over possible lifespans and future consumption streams is updated accordingly) and attention weight w^{yes} (which reflects an increase in attention that is increasing in the surprise associated with the change in belief). With probability $1-p$ the new cognitive state is defined by belief π^{no} and attention weight w^{no}, analogously. We posit that the desirability of the genetic testing is the expected utility of this new cognitive state minus the utility of the prior cognitive state. This change in utility can be decomposed into three parts, which we call instrumental value, motivated attention, and curiosity.

The instrumental value of genetic testing refers to the utility of future choices conditioned on knowing the test results minus the utility of future choices made without knowing the test results. Even though there is no cure for the disease, knowing that one has it has a significant impact on decisions such as whether to have children, when to retire, how much to save, how to invest, and whether to get or stay married (Oster et al., 2013). Standard economic arguments show that additional information can only improve decision making. Thus, the instrumental value of genetic testing is necessarily positive. The fact that genetic testing is rare despite little economic cost (Oster et al., 2013) suggests that one of the other sources of utility (motivated attention, we believe) is negative and significant. However, the instrumental value of medical testing cannot be ignored. If there were a medical treatment that would cure HD, genetic testing would no doubt be commonplace precisely because the information would be so instrumentally valuable.

Motivated attention to avoid genetic testing refers to the expected loss in utility associated with paying more attention to the belief about the HD gene in the cognitive state that arises after finding out the test result than in the prior cognitive state. Any change in belief attracts attention due to surprise. The less likely the individual considers having the HD gene to be, the more surprising it would be if the test does indeed reveal the gene. A "positive" test result would lead to a very negative belief, and having to think more about this negative belief would be very unpleasant. On the other hand, finding out that one does not have the gene would be a relief (certainly a gain in utility relative to one's prior expectation), but the belief might better be characterized as lacking negative valence rather than being intrinsically positive. The ex-ante expectation is that the new cognitive state will have lower utility because it will possibly involve thinking more about the unpleasant state of actually having the HD gene. (The new cognitive state will in the long run (after surprise wears off and importance diminishes with certainty) actually involve less thinking about having (or not having) the HD gene, but people are rarely sophisticated enough to foresee such adaptation. Moreover, the expectation of a loss in utility may not even be a conscious expectation but could arise as a learned response to situations in which one may find out bad news.) This is the key reason, we suggest, that genetic testing for the HD gene is rare.

Even though the overall level of genetic testing is infrequent, the rate of testing increases after symptoms of HD pop up (Oster et al., 2013). Oster et al. interpret this pattern as evidence of a correlation in the ex-ante risk of having HD and the propensity to get the test. Such a correlation could be accommodated in our model (because higher ex-ante probability of having HD implies that a positive test result would be less surprising and would thus lead to a smaller boost in attention on the bad news), but is not necessarily predicted by the model (because higher ex-ante risk also implies that bad news is more likely, so we have a countervailing effect as well). More fundamentally, though, the information-gap framework gives us a new perspective in which attention matters as much as probabilities, and this perspective calls into question whether the pattern of increased testing after symptoms arise really has to do with the ex-ante probability of having HD.

Observing a symptom of HD (or its absence) is itself an instance of acquiring information, which affects both the perceived probability of having HD and the attention to that possibility. In our framework, we could model the daily opportunities to observe symptoms (or the lack thereof) as a series of activated questions, Q_i, "Do I have a symptom on day i?". Having symptoms is obviously highly correlated with having the disease, but symptoms take time to manifest, so on any particular day i the probability of answering "yes" to question Q_i is low. This means that when a symptom pops up, it will produce a significant increase in the probability of having HD and it will be quite surprising, thus attracting extra attention to question Q. The extra attention could have two consequences: First, if there is a diminishing marginal impact of surprise on attention, it would weaken the marginal impact of additional surprise and thus weaken the impact of motivated attention as a reason to avoid testing (i.e., a person might think, "now that I'm worried I might have the disease, I can't avoid thinking about it, so I might as well find out"). Second, it would increase curiosity to find out if one has the disease (i.e., people would find it uncomfortable to wonder whether they have the disease, and the more they have to think about not knowing, the more curious they would be to find out). After observing a series of days without symptoms, by the same logic, the probability of having HD will have gradually decreased pretty significantly and none of these observations will be very surprising; so there would not be a large increase in attention to question Q. While a correlation in probability of having HD and propensity to test would suggest that patients in this situation exhibit even lower rates of testing, the data show no systematic variation in testing rates as asymptomatic individuals age (Oster et al., 2013).

The hypothesized belief-resolution effect offers us an additional testable prediction as well. If the relationship between observing symptoms and getting tested is due to changes in attention rather than changes in beliefs about the probability of having the gene, then it follows that individuals forced to wait a period of time after discovering symptoms before they could get tested (i.e., individuals who could adapt to the change in their circumstances) would be less inclined to get tested.