Too Much Information

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Abstract

We experimentally study how people's demand for information structures is shaped by their *informativeness*—the reduction in uncertainty they produce. To do this, we introduce new methods that remove confounds for information demand like failures of Bayesian reasoning. We show that people (i) strongly demand informativeness when it has instrumental value but also (ii) display a sharp aversion to informativeness when it cannot be used to improve choice, sometimes leading to costly errors in information choice. Several strands of evidence suggest that this aversion is driven by subjective information processing costs that rise with informativeness.

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1 Introduction

In this paper we experimentally study how people's demand for information structures is shaped by *informativeness*. Informativeness is the basic descriptive characteristic of information structures, measuring the reduction in uncertainty an information source is expected to induce (Frankel & Kamenica 2019). In standard economic theory informativeness influences information demand only to the extent that it produces instrumental value – i.e., to the extent that it is expected to improve decision making in relevant decision tasks. To the extent this is true, conditional on instrumental value, decision makers should be indifferent to informativeness and it should therefore have no direct impact on information demand. The goal of our paper is to treat this standard theoretical assumption as a null hypothesis, and compare it to two natural alternatives.

First, decision makers may directly value informativeness, above and beyond its contribution to instrumental value. That is, perhaps due to natural human curiosity, distaste for residual uncertainty, caution or deep-seated information-seeking heuristics that arise from the free disposal nature of information, people strictly prefer more informative information structures to less, even when holding instrumental value fixed. Second, it is possible that people instead display an *aversion* to informativeness that does not contribute directly to instrumental value. Richer (more informative) information structures are, after all, more complex in the sense that they require more intensive information processing to properly evaluate. If decision makers are unable (or unwilling) to bear the costs of fully understanding these structures, they may put a smaller premium on them relative to simpler (less informative) structures. Thus, an alternative hypothesis is that, conditional on instrumental value, demand for information falls with informativeness.

Studying people's demand for informativeness is difficult because it is easily confounded with other forces that shape and distort information demand. First, in typical *experimental* paradigms, the demand for information is confounded by well-known mistakes people make in *interpreting* and making use of information. Perhaps most importantly, most prior research on information in experimental economics is conducted in prior-signal updating settings in which subjects must apply Bayes' rule properly before they can *even understand* how a piece of information will influence their beliefs and actions. Because people have systematic tendencies to violate Bayes' rule, typical methods therefore run the risk of confounding systematic *confusion* about how information informs choice with *preferences* for information. Second, in typical *naturally occurring* observational settings, informativeness is easily confounded with drivers of taste for information that are difficult to theoretically operationalize and are therefore difficult to measure and control. For instance, sources of information may vary in how *entertaining* or *worrisome* they are, producing or inhibit-

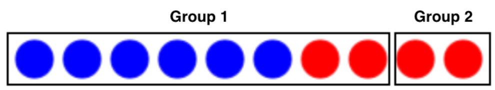


Figure 1: Example on the Representation of Information Structures in the Experiment *Notes: The subjects' task is to guess the color of a randomly selected ball. The information structure reveals whether the randomly selected ball is in Group 1 or Group 2.*

ing demand for information for reasons that have little to do with informativeness. These "affective characteristics" of information structures may be easily confounded with informativeness in ways that are difficult to formally account for in measurement exercises.

Our contribution is to propose and implement a method for eliciting preferences for information that is free from these confounds, allowing us to cleanly measure how informativeness shapes information demand. First, like most experiments in this literature, we study a simple setting in which subjects (i) must guess a binary state of the world (red or blue) but (ii) first receive a signal that may improve the accuracy of that guess. Because this experimental paradigm is completely abstract, variation in informativeness and instrumental value are unlikely to be confounded with affective characteristics of information (e.g., variation in how "entertaining" a source of information is) that might influence demand in uncontrolled or framed settings. Second, unlike most experiments, we present information in a way that doesn't require difficult applications of Bayes' rule. Instead, we present information as in Figure 1 by showing subjects (i) the prior as a set of ten balls (six blue, four red), one of which will be randomly selected to determine the true state and (ii) signals as subsets of these balls that, together, partition the ten balls (signals are drawn as boxes around balls – in the example the ten balls are partitioned into two subsets, so there are two possible signals). Subjects are told which subset the actually-selected ball is from before guessing the state. We find that this way of presenting signals entirely removes classical biases like over-under inference, motivated reasoning and confirmation bias: upon receiving a signal, subjects make the rational Bayesian decision (i.e., make an optimal guess about the color of the ball) 98% of the time.

We use these techniques to elicit subjects' preferences over sixteen distinct information structures, presented in this debiased way, with each structure corresponding to a unique partition. This variation across structures independently varies informativeness and instrumental value, allowing us to judge between our motivating hypotheses. We measure preferences in two ways. First, we elicit weak ordinal preferences by having subjects rank structures in order of preferences –higher-ranked information structures are more likely to be assigned to them for a payoff-relevent future choice, making the weak ranking incentive compatible. Second, we elicit strict cardinal preferences by eliciting subjects' willingness to pay to receive this information structure in a future choice, using an incentive compatible BDM mechanism (Becker, Degroot & Marschak 1964).

Our first main finding is that subjects' information preferences are strikingly sensitive to instrumental value. Subjects, on average, strictly prefer more instrumentally valuable information structures to less and sometimes reveal median valuations that are reasonably close to true instrumental value. However, we also find significant failures to rank information structures in terms of instrumental value and clear evidence that some information structures are significantly mis-valued.

Our second main finding is that conditional on instrumental value, subjects display a strong *aversion* to informativeness. When comparing two information structures with the same instrumental value, subjects tend to strictly prefer the less informative of the two. Indeed, our elicitations show that subjects are often willing to pay strictly less for information structures that are more informative. Using agnostic clustering techniques, we show that 2/3 of subjects display this strict aversion to informativeness (conditional on instrumental value) while a smaller cluster covering 1/4 of subjects displays behavior that suggests a preference *for* informativeness. We show that the dominant aversion to informativeness in the population is sometimes severe enough to make subjects prefer less instrumentally valuable information to more valuable alternatives. Indeed, our results suggest that aversion to informativeness is an important driver of failures to rank information structures according to instrumental value.

In the final part of the paper we examine *why* subjects display an aversion to informativeness that can't be used to improve choice. Our design allows us to rule out a number of salient hypotheses. First, we show that the results cannot be rationalized as an outgrowth of subjects' preferences for the timing of information: our results go in the opposite direction of recent measures of such preferences (Nielsen 2020). Indeed, our results suggest that this behavior is likely to be unrelated to uncertainty or risk preferences of any sort: our design includes a treatment in which we remove uncertainty (and with it preferences related to uncertainty) from these tasks while maintaining identical information processing in the valuation task, and document broadly similar results. Second, as discussed above, our design rules out classical inferential errors in assessing the information produced by these structures: subjects in our tasks show no signs of Bayesian errors like over-/under-inference, confirmation bias or motivated reasoning when making use of information. This means that aversion to informativeness can't be driven by rational anticipation of systematic mistakes in the use of information. Third, our design rules out the possibility that aversion to informativeness is due to inability to reason about how informative structures will be used to inform choice. In a diagnostic treatment, we have subjects make choices for every possible signal from every information structure *before* evaluating any of them, and remind subjects of these choices at the evaluation stage. Aversion to informativeness is no less strong in this treatment, suggesting that failures to contingently reason about the use of information does not underlie this result.

Instead, our results suggest that aversion to informativeness is a consequence of the fact that more informative structures are more costly to precisely evaluate and are therefore less well-understood by subjects, making them less attractive. Several pieces of evidence point towards this "complexity" interpretation, rooted in the costs and difficulties of evaluation. First, more informative information structures require significantly more time to evaluate than less informative structures: decision time or runtime is a direct resource cost of information processing that is often used in the literature (and throughout computer science) as a measure of complexity and effort.[1] Second, this is likely due to the fact that more informative information structures tend to consist of a larger number of strongly differentiated pieces of information that have to be *aggregated* in order to properly value them (e.g., they tend to contain more possible signals and induce more heavily differentiated distinct posteriors). Thus, in a very direct sense, properly valuing informative structures requires more work on the part of decision makers. Finally, we ran a treatment that removes uncertainty from information structures, leaving only the complexity of aggregating their features as a potential driver of misvaluations. We find similar aversion to "informative" structures in this data, strongly suggesting that the costs and difficulties of evaluation are the primary driver of this aversion to informativeness.

Taken together, our findings suggest that more informative information structures are less desirable, ceteris paribus, because they are more costly or difficult to evaluate, leading subjects to undervalue them. It is important to be clear that this is a ceteris paribus conclusion, made on the basis of a tightly controlled experiment designed to deliberately isolate important primitives of interest to information economics. Clearly, in applications many other characteristics of information that are harder to account for in economic theory compete with informativeness (and instrumental value) to shape information demand. For instance, people often pursue information that is informative but not instrumentally valuable because it is *entertaining* or *interesting*, leading them to demand informative but instrumentally useless trivia – characteristics that we do not yet know how to model, measure or control. Because of this, our experiment (like most experiments and indeed most models) deliberately brackets off these kinds of affective drivers of information demand in order to study the influence of primitives of information structures that we know how to measure and interpret. Doing this, we find that aversion to informativeness is substantial and sometimes

[1] Decision time is controversial as a complexity measure in some settings because subjects may choose to spend less time on more difficult problems (i.e., problems that seem too difficult to correctly solve). This is less of a problem in our setting because subjects virtually always make optimal decisions, conditional on information.

strong enough to cause subjects to prefer less instrumentally valuable information to more, leaving accuracy and earnings "on the table."

Our paper contributes to several literatures.

First, we make a methodological contribution to the growing experimental literature studying information demand. Our design allows us to study demand for information in a setting where making optimal use of information is very easy and does not require complex Bayesian reasoning. Thus, our visual representation of information structures successfully excludes non-Bayesian reasoning or misinterpretation of information structures as confounds for studying the demand for information. While we use these techniques to study informativeness, they can be easily applied to study many other questions about people's taste for information.

Second, our paper adds to a growing literature studying how factors other than instrumental value influence information demand. Prior studies have experimentally or theoretically examined the role of confirmation seeking (Charness, Oprea & Yuksel 2021, Montanari & Nunnari 2022), preference for certainty (Ambuehl & Li 2018, Novak, Matveenko & Ravaioli 2023), timing of resolution of uncertainty (Grant, Kajii & Polak 1998, Eliaz & Schotter 2007, 2010, Nielsen 2020, Falk & Zimmermann 2022, Je 2023), skewness of information (Masatlioglu, Orhun & Raymond 2023), anticipatory feelings (Caplin & Leahy 2001), motivated attention (Falk & Zimmermann 2022, Golman & Loewenstein 2018, Golman, Loewenstein, Molnar & Saccardo 2022), and behavioral motivations stimulated by changes in beliefs like disappointment aversion (Palacios-Huerta 1999, Dillenberger 2010, Andries & Haddad 2020), loss aversion (Koszegi & Rabin 2009), dissonance avoidance (Festinger 1957), suspense and surprise (Ely, Frankel & Kamenica 2015), etc., play in information demand. Our contribution to this literature is to study how demand is influenced by "informativeness", the basic descriptive characteristic of information structures. We show that informativeness has a powerful influence above and beyond its contribution to instrumental value. Because informativeness is a fundamental and universal characteristic of information structures, our findings have particularly wide-spread normative implications for information design and positive implications for predicting and interpreting information demand.

Most closely related to our study in this literature is Liang (2023), a concurrent paper that studies suboptimal valuation of information structures and provides evidence that is broadly supportive of the mechanism underlying our main results. In particular, his results suggest that subjects have difficulty foreseeing and integrating payoffs from multiple information-contingent choices, but it is mostly difficulties with integration which get in the way of optimal valuation. Specifically, in diagnostic treatments in which information-contingent choices are predetermined and presented as such, subjects behave more optimally. We also find suboptimal information demand that seems to derive from similar difficulties in evaluating information structures. Our results also link these types of difficulties in identifying instrumental value to informativeness.

Third our study provides a new kind of evidence in support of the central trade-off at the heart of rational inattention models: people acquire information to maximize utility net of information costs (Sims 2003, Matějka & McKay 2015, Caplin & Dean 2013). These models assume that decision makers face information costs that are (in typical parameterizations) increasing in Shannon mutual information between prior and posterior beliefs – the same measure of informativeness we use in most of our empirical work. Our paper contributes to this literature by expanding our understanding of when and why agents act as if information is costly. The rational inattention literature, strictly speaking, assumes that information costs are costs of information *gathering* or *extraction* (this is why they are called "inattention" models). For instance, state-of-the-art experiments on rational inattention typically ask subjects to extract information from complex visual images (Dewan & Neligh 2020, Caplin, Csaba, Leahy & Nov 2020, Dean & Neligh 2022) or from a series of equations (Ambuehl, Ockenfels & Stewart 2022). By contrast, we deliberately minimize information gathering costs by giving subjects direct and easily interpreted information on the state of the world. The fact that we nonetheless observe an aversion to informativeness suggests that information costs are not driven only by the cognitive effort required to *gather* or *extract* information, but are also driven by the cognitive effort required to *evaluate* the ex-ante value of information. Our results therefore suggest that rational inattention models may also be effective models of complexity (information processing) aversion, and may therefore have a much wider scope of application than is typically supposed.

Finally, our study relates to a growing literature showing the role complexity plays in a wide-range of economically important settings. Recent work suggests that people dislike engaging in complex behaviors (Oprea 2020), that this distaste has a strong distorting effect on choice (Banovetz & Oprea 2023), and that complexity limits and distorts the kinds of beliefs people form (Kendall & Oprea 2023). As a result, complexity (broadly defined as a cognitive processing costs) has been shown in recent work to be a major driver of behavioral anomalies in a number of canonical choice settings including, e.g., lottery anomalies (Enke & Graeber 2023, Oprea 2023), intertemporal choice anomalies (Enke, Graeber & Oprea 2023) and failures of Bayesian reasoning (Ba, Bohren & Imas 2023). Our work complements and extends this literature by providing evidence that valuations for a very different (but no less canonical) choice object (information structures) are also fundamentally shaped by complexity, leading to systematic anomalies in information demand.

The remainder of the paper is organized as follows. Section 2 presents our theoretical framework. Section 3 describes the experimental design. Section 4 presents results and Section 5 examines the mechanism driving these results. Section 6 concludes by discussing the implications of our results.

2 Theoretical Framework and Behavioral Hypotheses

2.1 Informativeness and Instrumental Value

Consider a finite state space Ω, with a typical state denoted by ω. The prior distribution on Ω is denoted by p. An information structure σ is a stochastic mapping from the state space Ω to a finite set of signals S. It is useful to think of σ as inducing a distribution over posteriors.[2] That is, given p, an information structure σ induces (i) a distribution q_σ over S and (ii) conditional on each signal s, a posterior distribution p^s_σ over the state space.

The amount of information generated by an information structure is described by a metric we will call its *informativeness*: the expected *reduction in uncertainty* induced by the information structure (see Frankel & Kamenica (2019) for an in-depth discussion). Several measures of informativeness can be defined because several metrics of "uncertainty" (and thereby "uncertainty reduction") can be selected for the purpose. For instance, the most prominent measure in the literature is based on Shannon entropy (Shannon 1948), a canonical measure of uncertainty in beliefs defined as $H(p) = -\sum_{\omega\in\Omega} p(\omega)\ln p(\omega)$. As characterized in Cabrales, Gossner & Serrano (2013), the *entropy informativeness* of information structure σ is the expected reduction of entropy of the decision-maker's beliefs as a result of the information conveyed by σ, that is, the Shannon mutual information between prior and posterior beliefs:

$$I_\sigma = H(p) - \sum_{s\in S} q(s)H(p^s). \tag{1}$$

This measure of informativeness is equal to zero when σ carries no information (posterior always equal prior) and is maximized at $H(p)$ when σ fully reveals the state. In summary, entropy informativeness provides a numeric measure of informativeness independent of the decision problem, allowing complete ordering of information structures. When studying "informativeness" we will focus on this entropy-based metric throughout the paper, but in Online Appendix F we show that little depends on this choice: our results are robust to varying the specific definition of informa-

[2]For each ω, let $\sigma_\omega(s) \in \Delta(S)$ denote the probability that signal s is realized. The probability of observing signal s is $q_\sigma(s) := \sum_\omega p(\omega)\sigma_\omega(s)$. For each signal, the posterior distribution on Ω can be computed using Bayes' rule. Conditional on each signal s, $p^s_\sigma(\omega) = \frac{p(\omega)\sigma_\omega(s)}{q_\sigma(s)}$.

tiveness we use.[3]

In standard economic theory, the value of an information structure to a decision-maker (DM) depends on the decision problem the information structure is meant to inform. Suppose the DM faces a decision problem in which she observes signal s from information structure σ and takes action $a \in A$ to maximize $\mathbb{E}[u(a,\omega)|s] := \sum p^s(\omega)u(a,\omega)$, where $u(a,\omega)$ describes the decision-maker's state-dependent utility function. The *instrumental value* (or simply *value*) of σ, given the set of actions A available and utility function u, is the expected increase in utility made possible by the DM being able to condition her action on the realized signals:

$$V_\sigma = \underbrace{\sum_{s \in S} q(s) \underbrace{\max_{a \in A} \mathbb{E}[u(a,\omega)|s]}_{\substack{\text{Expected utility} \\ \text{conditional on } s}}}_{\text{Expectation over } s} - \underbrace{\max_{a \in A} \mathbb{E}[u(a,\omega)]}_{\substack{\text{Expected utility} \\ \text{without } s}}.$$

Note that, when u is denominated in money, V_σ can further be interpreted as the the greatest price a rational decision-maker would be willing to pay for information from σ before facing a specific decision problem. Instrumental value is the key characteristic shaping information demand (i.e., preferences for information) in standard information economics.

Although informativeness and instrumental value are related, they are not the same thing. When comparing information structures σ and σ', it is possible for σ to be as (or even more) valuable than σ' while being less entropy informative. The reason for this is intuitive: in the context of any given decision problem it is possible for an information structure to reduce uncertainty in ways that are not useful for informing choice. This observation is what motivates our experiment.

2.2 Question and Hypotheses

Our question is how informativeness shapes people's preferences for (or demand for) information structures. As suggested above, economic theory gives a clear answer to this question: informativeness influences the demand for information *only* to the extent that it improves expected utility in a decision problem by allowing the decision maker to make better choices..

[3]For instance, an alternative ordering of informativeness across information structures is provided by Blackwell (1953). According to Blackwells ordering, an information structure is more informative than another whenever the latter is a garbling of the former, i.e., signals form the less informative structure can be interpreted as observing those from the more informative one with noise. Blackwell requires a strong condition for the comparison between information structures. By Blackwell's Theorem, a more informative structure (according to Blackwell ordering) generates higher instrumental value (as defined later in this section) in *any* decision problem. Thus, Blackwell provides only a partial order of informativeness, making it less useful for our purposes than entropy informativeness.

H0. Conditional on instrumental value, demand is not influenced by informativeness.

H0 hypothesizes that people evaluate information structures exclusively through the lens of the relevant decision problem that the information will be used to inform. An alternative possibility is that evaluation of information might be at least partially divorced from the specifics of the decision problem at hand. That is, it may be that decision makers' demand for information is influenced not only by the decision but also (at least in part) by characteristics of the information structure itself.

For instance, decision makers might prefer *more informative structures*, even when that informativeness is not useful for improving decision making. One reason for this might be that decision makers are drawn to more information as a hedge against the possibility that they've misunderstood how they would use that information. Or taste for informativeness might arise from rules of thumb, culled from natural life, that often instruct us to cautiously seek out information even when it is not immediately obvious how to use it. After all, information can always be disregarded if it doesn't prove to be useful. A final possibility is *curiosity* – a direct preference for more over less information in information sources (Golman & Loewenstein 2018, Golman, Loewenstein, Molnar & Saccardo 2022)– which might cause people to, ceteris paribus, prefer more informative information structures to less. We state this broad possibility as a second hypothesis:

H1. Conditional on instrumental value, demand for information is increasing with informativeness.

A final possibility is that people instead display an aversion to informativeness, particularly when additional information is not useful. Why might this be the case? Perhaps the most salient possibility is that information structures with high informativeness require more *information processing* and are therefore more costly to properly interpret and evaluate. That is, more informative structures may be more *complex* to process, using the definition of the term from computer science. Indeed, the idea that entropy reduction is costly to decision makers is an assumption often made in models of bounded rationality like rational inattention models (Sims 2003, Matějka & McKay 2015, Caplin & Dean 2013), though typically in settings somewhat different from ours. If decision makers are unable (or unwilling) to bear the costs of fully understanding these structures, they may put a smaller premium on them relative to simpler (less informative) structures, ceteris paribus. We state this possibility as a final hypothesis.

H2. Conditional on instrumental value, demand for information is decreasing with informativeness.

Our experiment, discussed below, is designed to distinguish between these hypotheses. In particular we designed our experiment to study (i) to what degree instrumental value predicts how people rank and bid on information structures and (ii) to what degree informativeness acts as an additional driver of information demand once its contribution to instrumental value is accounted for.

2.3 A Guessing Task

To study the questions posed above, we focus on a simple guessing task in our experiment. The state of the world is binary, i.e. $\Omega = \{b, r\}$, where b (as will be clear in the next section) can be interpreted as referring to the color *blue* and r referring to the color *red*. The decision-maker's prior is fixed at $p := p(b) = 0.6$. The decision-maker takes a binary action, $A = \{b, r\}$, with the goal of matching the state such that $u(a, \omega) = B$ (where B is a bonus) if $a = \omega$ and zero otherwise.

With this simple specification, the instrumental value of an information structure reduces to the following:

$$V_\sigma = \Bigg(\underbrace{\sum_{s \in S} q(s) \underbrace{\max\{p^s, 1-p^s\}}_{\substack{\text{Guessing accuracy} \\ \text{conditional on } s}}}_{\text{Expectation over } s} - \underbrace{p}_{\substack{\text{Guessing accuracy} \\ \text{without information}}} \Bigg) B. \tag{2}$$

Note that the expected utility of the decision-maker in this problem is equal to their guessing accuracy times the bonus associated with guessing correctly.[4] Thus, the value of an information structure for a decision maker-facing such a guessing task is directly linked to the expected improvement in their guessing accuracy. Although this setting is simple, as we will show in the next section, it is rich enough to allow us to construct a set of information structures that independently vary in instrumental value and informativeness, allowing us to test our hypotheses.

3 Experimental Design

3.1 Guessing Task and Representation of Information

We built our experimental design around the simple guessing task introduced in the last section. A random ball is drawn from a set of 10 which always consists of six blue balls and four red balls. The subjects' task is to correctly guess the color of that randomly selected ball. If they correctly guess the ball's color, they earn a bonus payment of \$10.

[4]For example, without additional information, the decision-maker guesses the state to be b (since $p > 0.5$). This guess is correct with probability p. Similarly, conditional on signal realization s, the decision-maker guesses the state to be the most likely state. Such a guess is correct with probability $\max\{p^s, 1-p^s\}$.

Before making their guess, subjects receive partial information about the randomly selected ball from an information structure. Each information structure is represented as a partition of the 10 balls. The information structure provides information about the randomly selected ball by revealing to the subject *which cell of the partition* the randomly selected ball belongs to. Thus, each cell of the partition is a distinct signal that the structure might generate. The size of any cell visually represents the probability with which that signal will be realized, and the composition of the balls within each cell visually represents the posterior probability that the ball is blue or red conditional on that signal being realized. Presenting information in this way therefore makes the characteristics of an information structure particularly transparent to subjects.

Figure 1 provides an example of an information structure that partitions the 10 balls into two cells (two possible signals). The first cell (labeled "Group 1") consists of six blue balls and two red balls; the second cell (labeled "Group 2") consists of the remaining two red balls. This information source provides information about the randomly selected ball by revealing which cell (Group 1 vs. Group 2) the randomly selected ball belongs to. Formally, the information structure generates a binary signal. The first (second) signal—corresponding to Group 1 (Group 2)—is realized with 80 (20) percent probability. Conditional on the first (second) signal, the posterior probability that the color of the randomly selected ball is blue is 75 (zero) percent.

We study a total of 16 information structures, depicted in Figure 2, which were selected to independently vary instrumental value and informativeness (as well as other characteristics). Table 12 in Online Appendix E provides a comparison of these information structures on both of these (and other) measures. For each of these information structures we (i) study how people make use of these information structures (by eliciting guesses for each information structure and signal) and (ii) study how people value these information structures (by eliciting rank preferences over and willingness-to-pay for these structures).

3.2 Eliciting Preferences for Information Structures

The main section of the experiment elicits subjects' preferences for the 16 information structures depicted in Figure 2 (we will call this the "Demand" section). We do this in two distinct ways, each of which has advantages and disadvantages. Figure 3 shows screenshots of each.

Ranking: Subjects are asked to rank the 16 information structures from most preferred to least preferred. Specifically, the 16 structures are presented to subjects (in an order randomized on the individual level) and subjects are tasked with reordering them using a drag-and-drop interface. Sub-

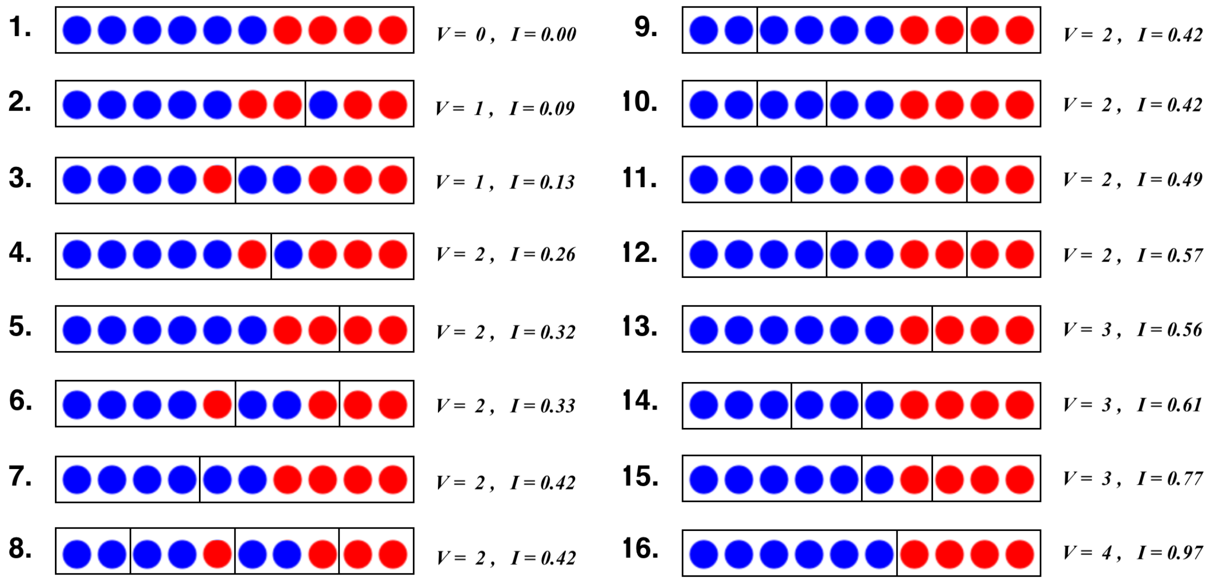


Figure 2: The 16 Information Structures used in the Experiment *Notes: The information structures are listed lexicographical in order of instrumental value (V as defined in equation 2) and entropy informativeness (I as defined in equation 1) . To make the partitions more salient in the experiment, each cell of the partition was labeled as "Group 1", "Group 2," etc. See Online Appendix E for details on other characteristics of these information structures.*

jects are incentivized to place more preferred information structures above (higher in the list than) less preferred structures: structures that are placed higher on the list are more likely to be assigned to subjects for a paid guessing task that occurs at the end of the experiment. The advantage of the Ranking elicitation is that it is extremely simple and intuitive for subjects, likely providing cleaner evidence of rank preferences. The disadvantage is that, strictly speaking, this method measures only a weak preference ordering: subjects who are indifferent between two structures nonetheless must rank one higher than another.

WTP: After ranking information structures, subjects are given an endowment of \$5 and shown the information structures in the order they ranked them. For each of the 16 information structures, subjects are then asked to express (using a slider) their (maximum) willingness to pay (WTP) to receive information from that structure in a guessing task that will occur at the end of the experiment. Incentives are provided using the Becker-Degroot-Marschak (BDM) method (Becker, Degroot & Marschak 1964) and if subjects do not purchase the information structure, they will receive no information to inform their guess. The advantage of the WTP elicitation is that it measures strict preferences. The disadvantage is that elicited WTP (using BDM and related mechanisms) is much more complicated than Ranking, and is therefore known to be noisy and subject

(a) Ranking

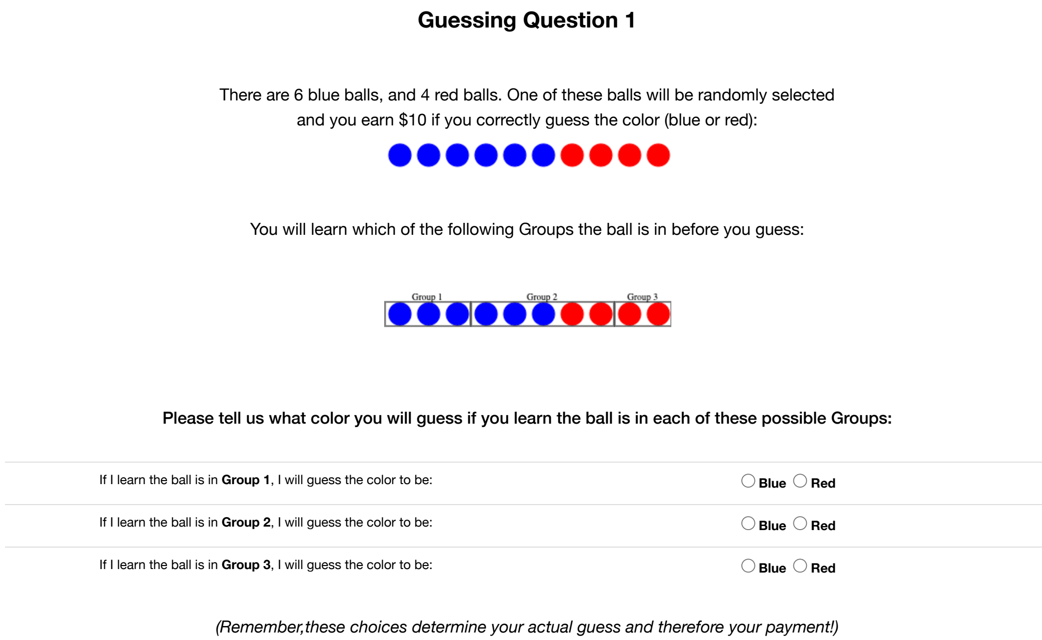
(b) WTP

Figure 3: Eliciting Demand for Information

to biases (in particular, the pull-to-the-center effect in Danz, Vesterlund & Wilson (2022)).[5]

We will make use of each of these elicitations in our analysis for robustness, allowing each method to compensate for weaknesses of the other. In some of our analysis we will do this in an explicit

[5]WTP elicitation also gives us quantiative measures of value that can be compared to theoretical benchmarks. For a risk neutral agent, WTP should be $10 times the increase in guessing accuracy enabled by each information structure (as captured in Equation 2). In Online Appendix A, Figure 12 shows that the WTP of a reasonably risk averse or loving agent does not deviate much from the WTP of the risk neutral agent. In much of our analysis we focus on relative comparison of WTP amounts (whether a subject is willing to pay more for one information structure relative to another). These comparisons should be determined entirely by instrumental value (as defined by Equation 2) independent of risk preferences, under standard theory.


Guessing Question 1

There are 6 blue balls, and 4 red balls. One of these balls will be randomly selected and you earn $10 if you correctly guess the color (blue or red):

You will learn which of the following Groups the ball is in before you guess:

Group 1 Group 2 Group 3

Please tell us what color you will guess if you learn the ball is in each of these possible Groups:

If I learn the ball is in **Group 1**, I will guess the color to be:	○ **Blue** ○ **Red**
If I learn the ball is in **Group 2**, I will guess the color to be:	○ **Blue** ○ **Red**
If I learn the ball is in **Group 3**, I will guess the color to be:	○ **Blue** ○ **Red**

(Remember,these choices determine your actual guess and therefore your payment!)

Figure 4: Elicit Guesses

way. Because of known noisiness in WTP elicitations, when comparing WTP between different information structures, in addition to reporting aggregate results, we will also report results for the subset of observations in which WTP comparisons agree with the ordering elicited in the simpler (and arguably therefore more reliable) Ranking elicitations.

3.3 Eliciting Guesses

In the Guesses section of the experiment, we ask subjects to make a guess of the ball's color for each possible signal in each of the information structures depicted in Figure 2. Figure 4 shows a screenshot from this task. We remind subjects of the task and incentives and then show subjects a partition of the blue and red balls, labeling each element as a "group." At the bottom, subjects are asked to give their guess of the ball's color for each possible group the ball might be in (for each possible signal they might receive).

The purpose of the Guesses section of the experiment is to study how people make use of information from information structures and whether subjects use that information in a suboptimal way. This information is important for interpreting subjects' demand for information structures.

3.4 Treatment Variations

In our **Baseline** treatment ($N = 109$ subjects), we ask subjects to perform the Demand section of the experiment (the Ranking and WTP elicitations) first, and the Guesses section afterwards. To this we add two diagnostic treatments that will help us to interpret our results.

First, in our **Reverse** treatment ($N = 54$ subjects), we reversed the order: subjects were assigned Guesses first and Demand afterwards. In these sessions, during the Demand section, subjects were actually shown the guesses they had made earlier, conditional on each possible signal for that information structure.[6] This information was not binding, but was designed to remind subjects of how different signal realizations are likely to generate different guessing patterns. The purpose of this treatment was to study whether having already made use of information structures (and being reminded of how they are used) improves subjects' identification of instrumental value in guiding their demand. This will be useful for understanding the mechanism behind our results.

Second, in our **No Uncertainty** treatment ($N = 61$ subjects), we removed uncertainty from the design using techniques employed by Martinez-Marquina, Niederle & Vespa (2019) and Oprea (2023). Specifically, instead of drawing only one ball, we informed subjects that we would draw *all balls* and pay subjects based on the accuracy of their guess for each of the balls.[7,8] Everything else in the experiment remains identical. Doing this retains much of the information processing involved in evaluating and interpreting information structures, but removes scope for risk, uncertainty or timing preferences (e.g., preferences for the timing of the resolution of information). Again, this data will be useful for understanding the mechanism behind our results.

3.5 Incentives and Implementation Details

All sessions were conducted at the LITE laboratory at the University of California, Santa Barbara between December 2021 and March 2023. We recruited subjects from across the curriculum to participate in 15 sessions using the ORSEE recruiting software (Greiner 2015). The experiment was conducted using software programmed by the authors in Qualtrics. Between 8 and 21 subjects participated in each session and sessions lasted for 30-40 minutes.

[6]See Figure 18 in Online Appendix G for a screenshot how this was displayed to subjects.

[7]In this case, the partition associated with an "information" structure constrains the types of guesses subjects can make by requiring them to make the same guess for all balls in the same cell of the partition.

[8]To achieve a clean comparison to the other treatments, subjects received a prize of \$1 for each of the balls for which their guesses were correct. This implies, for example, an information structure that enables a guessing accuracy of 90 percent will generate the same expected bonus payment in all three treatments.

All subjects received a show up fee of $7. Subjects' earnings depended on a randomly selected section of the experiment. If the Demand section was selected for payment, we randomized between Ranking and WTP. If Ranking was selected, two information structures (from the set of 16) were randomly selected and the subject was assigned to receive information from the one that was ranked higher. If WTP was selected, one information structure (from the set of 16) was randomly selected and whether or not the subject received information from this source was determined according to the BDM mechanism. In either case (regardless of whether Ranking or WTP was selected), at the end of the experiment, the subject was presented with one additional guessing task with information from the selected information structure and subjects were paid based on this guess.[9] If the Guesses section was selected for payment, a random information structure was picked and the subject's guesses for that case were used to determine payment for a randomly drawn ball. Note that in all cases, whether or not subjects received a bonus payment of $10 ultimately depended on the accuracy of their guess about the color of a randomly selected ball.

4 Results

4.1 Optimality of Guesses

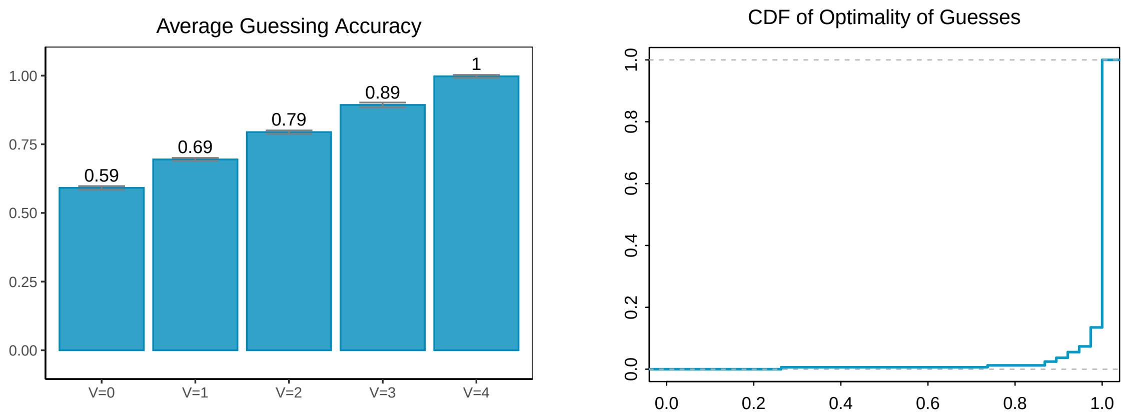
We begin by confirming that our experimental design successfully removes inferential errors like failures of Bayesian reasoning when subjects use signals from information structures.[10] To do this, we study how subjects make use of the information provided to them. We focus on two measures. The *accuracy* of subjects' guesses is the likelihood that those guesses match the state (the true color of the randomly selected ball). The *optimality* of subjects' guesses is the likelihood with which subjects' guesses are optimal given the signal realization.[11]

Figure 5a presents data on guessing accuracy, and shows how this varies with the instrumental value of the information structure. Note that subjects start with a prior of 0.6; hence, in the absence of any information, we would expect guessing accuracy to be equal to this value if guesses are optimal (i.e. if they guess the color of the ball to blue). We find, indeed, guessing accuracy to be 0.59 in this case. With information structures that are capable of improving guessing accuracy

[9] Note that this could mean the subject receives no information depending on the subject's WTP if WTP is selected.

[10] As we show in Section 5, none of our results are impacted by the order with which subjects are assigned the Guess and Demand tasks. For this reason, throughout this section, we will pool the Baseline and Reverse treatments; all of our results continue to hold if we instead focus on the Baseline treatment alone.

[11] To allow for clean interpretation of this measure, we restrict attention to signals (with Bayesian posterior different from 0.5) for which there is a unique optimal guess.



(a) Guessing Accuracy by Value

(b) Distribution of Optimality of Guesses

Figure 5: Optimality of the Use of Signals *Notes: In panel (a) V denotes instrumental value (see Equation 2 for formal definition). Gray lines denote 95 percent confidence intervals. In panel (b) optimality of guesses is computed on the individual level and denotes the share of signals for which guess was optimal.*

by 10, 20 or 30 percent, we find that guessing accuracy increases to 0.69, 0.79 and 0.89. When the information structure is fully revealing, guessing accuracy goes up to 1. Thus, subjects make near-perfect use of information structures to inform guessing accuracy.

Figure 5a shows the optimality rate of guesses, and depicts the distribution of this measure—the share of signals for which the subject's guess is optimal—computed at the individual level. A vast majority of subjects (86 percent) *always* make optimal choices. Overall 98 percent of guesses are optimal conditional on the information available to the subjects. This near-perfect optimality strongly suggests that our methods for providing information avoid Bayesian errors (and other errors like confirmation bias), removing a major barrier to measuring information preferences.

Result 1. *Subjects make near optimal use of information. Guesses conditional on signal are optimal 98% of the time. 86% of subjects make optimal guesses 100% of the time.*

4.2 Demand for Information

Figure 6 provides a first look at how demand for information is shaped by instrumental value and informativeness, by examining data from our elicitations. Panel (a) of the Figure examines all pairwise ranking comparisons between information structures in which the one structure is strictly more instrumentally valuable than the other. The bars show the likelihood with which the more instrumentally valuable structure was ranked higher than (as more preferred to) the second. We plot a separate bar for cases in which the value difference is weakly below the median for the dataset ($\Delta_v = 1$) or strictly above the median ($\Delta_v > 1$). When the value difference is relatively low, the optimal structure is preferred 72.7 percent of the time. This increases to 85.3 percent when the value difference is relatively high.

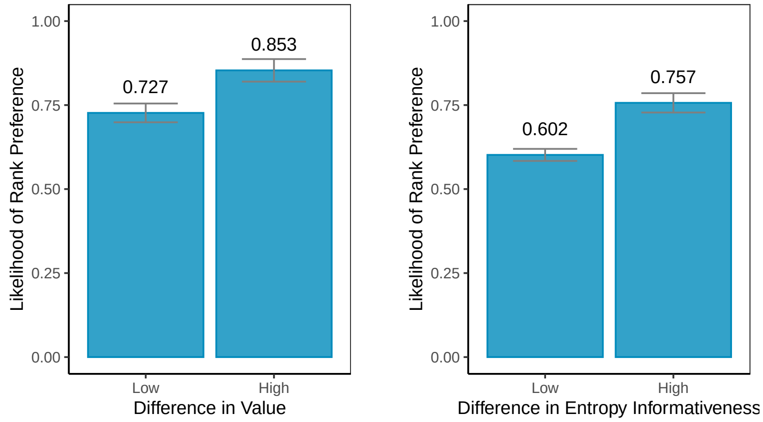
Panel (b) of the same Figure studies how often subjects display a preference for the more *informative* information structure, among all of the pairwise comparisons in which structures can be ranked by informativeness. As in panel (a), the "low" bar represents pairs of information structures in which the difference in informativeness is relatively low (weakly below the median difference of 0.24), while high represents the cases where the difference is high (strictly above the median difference of 0.24). When the difference in informativeness is low, the more informative structure is preferred 60.2 percent of the time. This increases to 75.7 percent when difference in entropy informativeness is high.[12] Thus, in uncontrolled comparisons, subjects tend to prefer more informative to less informative information structures.

Figure 6 confirms that demand for information is strongly predicted by its instrumental value. We show the same thing in a more disaggregated way in Figure 7 by plotting the distributions of responses (for both Ranking and WTP) by the instrumental value of the information structure. The plot shows that 58 percent of subjects treat information structure 1 (see Figure 2), which has zero instrumental value, as the least preferred information structure and 83 percent of subjects treat information structure 16, which has the highest possible instrumental value (by fully revealing the state), as the most preferred information structure. Overall, there is first order stochastic dominance between distributions whenever we compare information structures with low value to high value. Similar patterns are also observed in the distribution of WTP amounts.[13]

Although these results show that (as expected) instrumental value is a major driver of information demand, they also reveal significant deviation from payoff maximizing behavior. As Figure 6 shows, in 27.3 percent of relevant cases, subjects rank a less intramentally valuable information structure higher (i.e., as more preferred) than a more valuable information structure when the value difference is relatively low. Even in such cases these mistakes come at significant cost to subjects. By ranking less valuable structures as more preferred, conditional on the pairwise comparison being

[12]Here and throughout the results we will focus on measures of "entropy informativeness." However in Appendix F, we show that these results also hold with alternative ways of comparing informativeness, including Blackwell ordering and the variance of posterior.

[13]There are some deviations from this pattern in WTP for information structure 16 with value of 4. As expected, the WTP data also displays clear compression often seen with BDM elicitations: subjects on average overpay for information structures of low value and underpay for information structures of high value.



(a) (b)

Figure 6: Demand for Information by Value and Informativeness *Notes: The figures condition on all pairwise comparisons between information structures where there there is a strict positive difference—on value for (a) or entropy informativeness for (b)—between the first and the second structure. See Section 2 for formal definitions of value and informativeness. The bars depict the likelihood with which the first structure was ranked as more preferred to the second.* Low *(*High*) represents all pairwise comparisons where the difference is weakly lower (strictly higher) than the median difference: 1 for value, and 0.24 for entropy informativeness. Gray lines denote 95 percent confidence intervals.*

relevant for payment, subjects reduce their guessing accuracy by 10 percent (22 percent) in *Low* (*High*) cases, leaving approximately \$1 (\$2.2) on the table.[14] Such mistakes are less frequently observed (14.7 percent) when the value difference is higher, but in these cases the mistakes are also twice as costly.

Result 2. *Demand for information is strongly influenced by its instrumental value, but there are serious deviations from payoff maximizing behavior. Subjects also tend to prefer more informative structures to less informative structures in the raw data.*

4.3 Preferences for Informativeness

We now turn to our main questions, by evaluating the hypotheses posed in Section 2.2. In the raw data (e.g., Figure 6) subjects show a clear preference for more informative information structures, but this measure is confounded with instrumental value. To separate the two notions, we study "excess informativeness": informativeness that does not improve instrumental value, measured by examining the effect of informativeness on information demand in comparisons that hold instrumental value fixed.

[14]To compute this, we look at subjects' expected bonus payment conditional on each information structure for each of these violations.

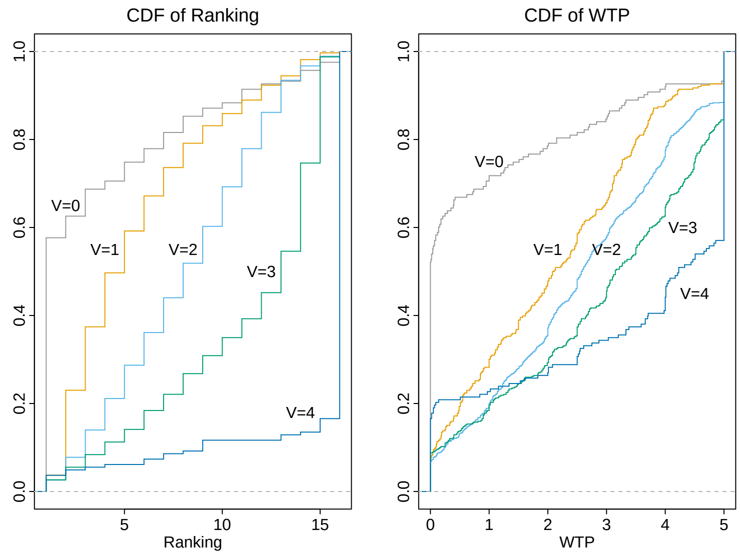


Figure 7: Distribution of Rank and WTP by Value *Notes: When subjects order information structures, each structure is assigned a ranking from 1 (least preferred) to 16 (most preferred). V denotes the value of an information structure as defined in equation 2.*

Figure 8 gives us a first view of the effects of excess informativeness on information demand. Each data point in the Figure represents a pair of information structures. Due to symmetry, we focus on pairs in which the "first" information structure in the pair has a weakly higher value than the "second" one. On the x-axis of both panels we plot the difference in informativeness between the two structures. On the y-axis we plot (i) the likelihood that the weakly higher-value structure is ranked higher in the Ranking elicitation (in the left hand panel) and (ii) the difference in WTP in between the weakly higher and lower value structures (in the right hand panel).[15] We separate the data points (by color and shape) based on the value difference, Δ_v between the two information structures. We also separate out (and show in faded colors) pairs in which at least one information structure is visually disordered (i.e. blue and red balls are not shown in orderly clusters) in order to account for the higher visual complexity of these tasks.[16] The graphs also depict linear fits: gray

[15]WTP data is inconsistent with ranking data in 25 percent of pairwise comparisons. These are cases where one structure is ranked as more preferred to another, but WTP for the former is strictly lower than the other. Many features of the data suggest that Ranking data is a better representation of subjects' preferences than WTP: (i) Subjects on average spend 50 percent more time on Ranking than WTP; (ii) in cases where Ranking and WTP data are inconsistent, value difference is predictive of relative ranking ($p < 0.01$), but not differences in WTP. This is not surprising given the typical noisiness of WTP elicitations in the literature. Thus, to facilitate stronger interpretation of the results, in Online Appendix F Figure 17 we re-conduct the analysis of WTP restricting attention to WTPs that are ranked consistently with the Ranking data. We find very similar results in this analysis.

[16]While this was not anticipated at the design stage, the results clearly reveal subjects to have an aversion towards information structures that are visually disordered (as seen in regressions reported in Online Appendix F Table 16).

lines include all pairs within a value-difference class, darker lines in the corresponding color restrict attention to pairs within each class where there is no visual disorder, hence providing us with the cleanest comparison.

The results show striking evidence in support of Hypothesis 2: demand for information decreases with informativeness when we control for instrumental value. Focusing first on pairs with identical instrumental values ($\Delta_v = 0$) plotted with green squares, we find that as an information structure becomes more informative (relative to an alternate structure) it (i) becomes less likely to be ranked more highly than the alternative information structure (left panel) and (ii) has a smaller WTP assigned to it relative to the alternative structure (right panel). What is even more striking is that the same pattern is also observed when we look at pairs in which the instrumental value difference between the two information structures rises to 1 (blue circles). Payoff maximizing behavior here requires the high value information structure to be preferred to the low value one with 100 percent probability (left panel). While this instrumental value difference clearly increases the likelihood of preference for the higher value structure (blue circles are almost always above the green squares, conditional on informativeness difference), the likelihood is substantially below one in most of these cases. Furthermore, the likelihood decreases (generating more violations of payoff-maximizing behavior) as the informativeness of the more valuable information structure increases. Similar patterns are observed when we focus on relative WTP (right panel). Eventually, once the instrumental value difference between the two information structures increases to 2 or more (purple or gray triangles, respectively), the pattern disappears for rank preference (left panel) suggesting that instrumental value eventually overtakes the negative effect of informativeness in rankings. While differences in WTP between the two information structures increase substantially when the value difference increases to 2 or more, we still observe the pattern that difference in WTP is decreasing as the informativeness of the more valuable information structure increases (right panel).[17]

In Table 1 we provide statistical support for these results by examining pairs of information structures and regressing Rankings (using Logit) and WTP differences (using OLS) on (i) the difference in instrumental value between the two structures and (ii) the difference in informativeness.

This seems consistent with findings on order-preference that cannot be explained by consumption utility in Evers, Inbar, Loewenstein & Zeelenberg (2014).

[17] Another important observation on Figure 8 is that the WTP data is much noisier than the ranking data (although it produces the same qualitative patterns). For example, when the value difference between two information structures is 2 or higher, subjects rank the more valuable one as more preferred about 85 percent of the time. While the average WTP for the former one is \$1.2 higher than the other one (p-value<0.001), the aggregate likelihood that the WTP for the former is higher than the other one (by more than 10 cents when it should be around \$2) is only 67 percent.

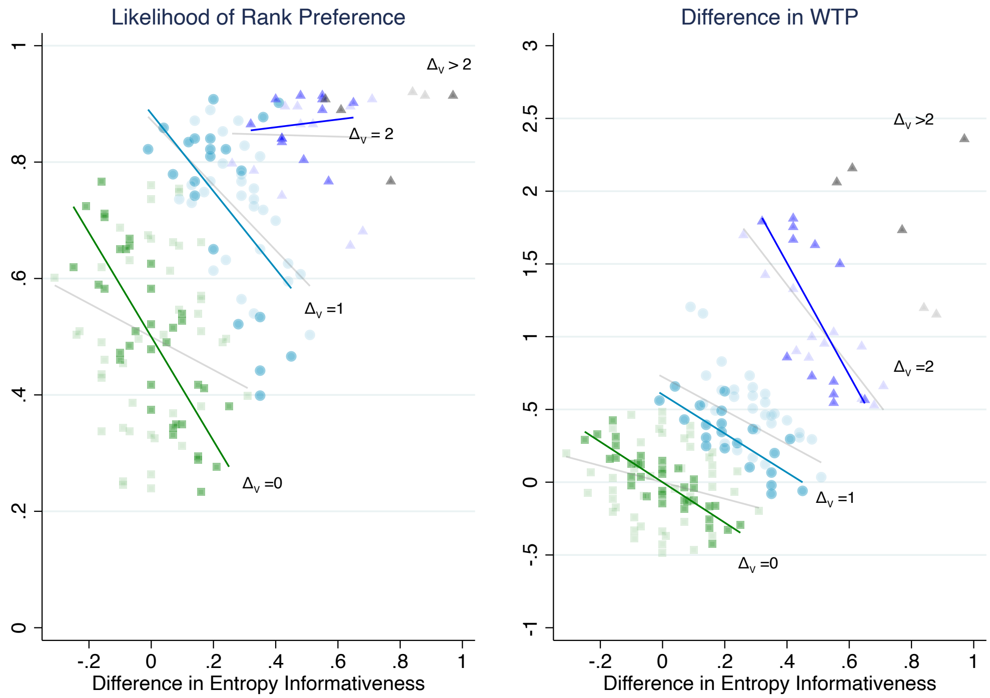


Figure 8: Preference for Information Structure by Value and Informativeness *Notes: Each dot denotes a pair of information structures. Green squares denote pairs where there both information structures are of the same value. Blue dots denote pairs where the value difference between the first and second information structure is 1. The darker blue (gray) triangles denote pairs where the value difference is equal to (larger than) 2. To account for the potential impact of visual complexity, pairs with at least one information structure where the blue and red balls are not displayed in order are depicted in a lighter color. Gray lines depict the best linear fits for each of the first three categories. Darker lines in the corresponding colors denote the best linear fits where the pairs depicted in a lighter color are not included.*

When we include these as dependent variables individually, we find exactly what we documented in the previous subsection: that both relative Ranking and differences in WTP are significantly increasing in both differences in instrumental value and informativeness. However, when we include both variables, controlling for instrumental value, the coefficient on informativeness becomes negative and highly significant, indicating demand that instead decreases in informativeness. Thus, when we control for instrumental value, we find strong evidence that informativeness decreases demand for information as visualized in Figure 8. Detailed results are presented in Online Appendix F Table 16.[18]

[18]Since informativeness and value are necessarily correlated, in Table 17 of this Online Appendix, we also include separate regressions with only differences in entropy informativeness and visual disorder as right-hand-side variables for different classes of information structure pairs that are separated by value difference. The regressions further support the main conclusions of this section. In Tables 18-19 of this Online Appendix, we also show that these results are not driven by the specific measure of informativeness used in the analysis: aversion to more information

Table 1: Determinants of Demand for Information

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	0.800***		1.607***	0.527***		0.924***
	(0.063)		(0.150)	(0.046)		(0.104)
Difference in Informativeness		2.453***	-3.436***		1.812***	-1.716***
		(0.193)	(0.487)		(0.167)	(0.338)
Clusters	163	163	163	163	163	163

*Notes: See Section 2 for formal definitions of value and entropy informativeness. Regressions control for differences in visual disorder (whether the blue and the red balls were presented out of order). Detailed results are presented in Online Appendix F Table 16. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

To better understand these results, Figure 9 shows some especially diagnostically valuable examples from the dataset. Information structures 14 and 15 have the same instrumental values, inducing guessing accuracy of 80 percent, but 15 is more entropy informative (it also dominates 14 according to the Blackwell ordering). This is easy to verify visually. 15 generates the same posterior as 14 for the first five blue balls, but breaks down the posterior of 20 percent conditional on the remaining balls into two distinct posteriors: 50 percent with 40 percent probability and zero percent with 60 percent probability. Subjects, in the aggregate, prefer 14 to 15: 77 percent of subjects rank the former as more preferred than the latter one.[19] The comparison of these information structures to information structure 10, which is less instrumentally valuable (inducing guessing accuracy of only 70 percent) reveals that the negative impact of informativeness on information demand can be large enough to distort valuations relative to instrumental value. 81 percent of subjects rank 14 as more preferred than 10, making an earnings-maximizing choice. However, when the more informative 15 is compared to 10, only 40 percent of subject rank 15 higher. In other words, 60 percent of subjects behave suboptimally when comparing 15 to 10. This suggests that informativeness can distort subjects' evaluation of information structures to the degree that it generates violations in how information structures are ranked relative to instrumental value – a finding that is mirrored in the aggregate statistics.

controlling for value is also seen when we compare informativeness of information structures using the Blackwell order or the variance of the induced posteriors (see Frankel & Kamenica (2019) for further discussions on these alternative comparisons of informativeness).

[19]The example suggests that the negative impact of informativeness on information demand might be due to an aversion to signals that are maximally uncertain (associated with a posterior of 0.5). We discuss this possibility in relation to other alternative explanations in Section 5.1.

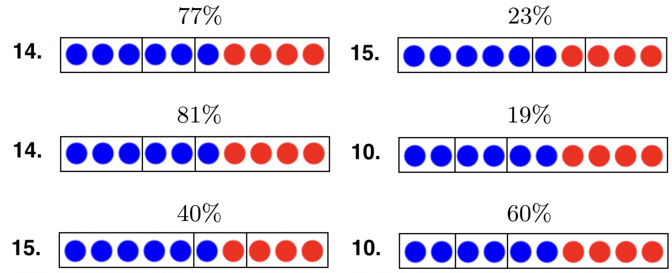


Figure 9: Example of Aversion to Informativeness *Notes: The percentage of subjects who rank an information structure as more preferred to the other (shown on the same row) is displayed above the information structure.*

We summarize the main result of this section as a third result:

Result 3. *Controlling for instrumental value, subjects display a preference for structures that are* less *informative. High informativeness decreases demand, and increases the likelihood of suboptimal demand.*

The negative impact of informativeness on information demand is important, because it generates "mistakes" in valuation relative to instrumental value. Indeed, our results suggest that informativeness that does not contribute to instrumental value is an important driver of suboptimal demand in our data.

4.4 Heterogeneity

Our results so far have been based on an aggregate analysis. Does demand for information vary with informativeness and instrumental value similarly for all subjects? To find out, we examine heterogeneity by classifying subjects into types using clustering analysis. Since there are many possible factors driving preferences over information structures in our setting, we take an agnostic approach, using clustering to seek out "natural" groupings in the data without reliance on labeled examples of what prominent types might be in the data.[20]

Specifically, we transform subjects' rank preference to 120 pairwise comparisons, recording which information structure was preferred in each possible pair. We then fit a Bernoulli Mixture Model (BMM) pre-specifying the number of clusters $k \in \{2, 3, 4, 5, 6\}$.[21] Then we select the number of clusters k associated with the lowest BIC (Bayesian information criterion). This method

[20]Recently, Charness, Oprea & Yuksel (2021) used a similar approach in an experiment on information demand (focused on how people interpret biased information structures). They found that heterogeneity was important for understanding information preferences in their data. In particular, this type of analysis revealed an important minority cluster of subjects who behaved in a way that was systematically different than aggregate behavior.

[21]Choice of the BMM model is natural here as it is developed specifically for clustering of multidimensional binary

partitions our subjects into 4 clusters. In order of size, the first cluster covers 74 subjects (45% of the data), the second cluster 40 subjects (25% of the data), the third cluster 35 subjects (21% of the data), and the fourth cluster 14 subjects (9% of the data).

Table 6 in Online Appendix D compare subjects in these different clusters in terms of the optimality of their guesses and their rankings of information structures. The largest two clusters are very similar, displaying high optimality on both dimensions, matching central tendencies in our aggregate analysis. While guesses are highly optimal for the third cluster, optimality of the ranking of information structures weakens significantly for this group. Finally, the smallest fourth cluster is particularly noisy on both dimensions. For this reason, we focus our analysis in the main text to the biggest three clusters (91 percent of our subjects) and relegate corresponding analysis of the smallest cluster to Online Appendix D.

Figure 13 in Online Appendix D reproduces Figure 8 separately for each of the main clusters in our data. The most striking observation is the contrast in behavior between the first two clusters. In the largest cluster, demand for information is decreasing in informativeness once we control for value, matching our aggregate findings. This is reflected in both Ranking and WTP data. The second cluster displays the opposite behavior (at least when focusing on Ranking data): controlling for value, subjects in this cluster display a preference for more informativeness, however there is weaker evidence for this in WTP data. Patterns observed in the third cluster are reminiscent of those from the first cluster (at least with respect to sensitivity to informativeness), but behavior is noisier and as noted above, there are more deviations from optimal behavior. Table 2 provides further support for these observations using regression analysis (reproducing Table 1 separately for the largest three clusters). We find that relative Ranking and differences in WTP are both significantly *decreasing* in informativeness when we control for instrumental value for the first and the third clusters, but the opposite result is observed (at least when focusing on relative ranking) for cluster 2.[22]

data. This clustering method first estimates parameters of the subpopulations (mixture components), each being a multidimensional Bernoulli distribution, and weights of each subpopulation (mixture weights). Then, using these estimates, clustering simply becomes a matter of using Bayes' rule to classify each observation as belonging to the mixture component most likely to have produced it.

[22]Using different clustering methods (such as K-Modes clustering) generates similar results. See Online Appendix D for further details.

Table 2: Determinants of Demand for Information By Cluster

	Ranking (Logit)			Difference in WTP (OLS)		
	C1	C2	C3	C1	C2	C3
Difference in Value	3.744***	0.809***	1.085***	1.425***	0.548***	0.617**
	(0.164)	(0.182)	(0.170)	(0.162)	(0.115)	(0.237)
Difference in Informativeness	-9.855***	2.942***	-2.843***	-3.189***	-0.148	-1.332*
	(0.638)	(0.755)	(0.651)	(0.523)	(0.439)	(0.786)
Clusters	74	40	35	74	40	35

*Notes: C1, C2 and C3 refer to Clusters 1, 2 and 3 and represent 45%, 25% and 21% of the data, respectively. See Section 2 for formal definitions of value and entropy informativeness. Regressions control for differences in visual disorder (whether the blue and the red balls were presented out of order). Detailed results are presented in Tables 7 - 9 in Online Appendix D. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Overall, in the first and the third clusters (covering 67 percent of our data) demand for information is decreasing in informativeness when we control for instrumental value, while we find no evidence for such a tendency in the second cluster (25 percent of the data) which shows some evidence of preferences for more informativeness. It is worth emphasizing that the clustering method does not assume in any way that informativeness should play a role in how subjects are classified into different types. Thus, these results strongly reinforce our finding that the influence of informativeness on information demand plays a key role in organizing heterogeneity in our data.

Result 4. *For a majority of subjects, demand for information is* decreasing *in informativeness when controlling for its instrumental value.*

5 Mechanism

Why is demand for information decreasing in informativeness, ceteris paribus, for a majority of subjects in our data? In this section we use data from diagnostic treatments and analysis of auxilary data to answer this question. In Sections 5.2 and 5.1 we provide evidence that rules out explanations rooted in subjects' preferences over timing of the resolution of uncertainty or risk or misunderstandings of how to make use of information structures. In Section 5.3 we instead present evidence that aversion to informativeness is likely a consequence of the fact that informative information structures are more costly to evaluate properly (i.e., are more "complex" to value). As a result, subjects avoid these information structures and are instead drawn to less informative ones, sometimes leaving instrumental value "on the table" in order to avoid these information processing costs.

5.1 Timing and Risk Preferences

One natural class of explanation for aversion to informativeness is non-standard preferences over risk, loss or the timing of the resolution of uncertainty. We find that preference-based mechanisms of this sort cannot explain our data, for two reasons. First, our data does not seem to fit with the most promising such explanations, given prior empirical findings. Second, we designed our No Uncertainty treatment to shut down scope for such preferences altogether and we find results that are broadly similar to those from our main treatments.

Perhaps the most relevant preference-based mechanism given our experiment is that subjects might have preferences over the timing of the resolution of uncertainty (e.g., Kreps & Porteus (1978), Grant, Kajii & Polak (1998)). Prior experimental results have shown that subjects have seemingly strict preferences for earlier revelation of non-instrumental information from information structures (Eliaz & Schotter 2007, 2010, Nielsen 2020, Falk & Zimmermann 2022). However, our results seem to show the exact opposite: subjects display a preference to *avoid* non-instrumental information (i.e., informative structures that don't improve choice), which means subjects reveal (if anything) a preference to delay learning about the true payoff state.

Other preference-based explanations seem similarly unlikely to fully account for our results. For instance, in our setting, loss aversion (Koszegi & Rabin 2009) could possibly manifest as an aversion towards information structures which generate maximally uncertain signals (with associated posterior of 0.5) as such signals imply a lower likelihood of winning the prize than the prior.[23] Our main results on informativeness aversion (controlling for instrumental value) remain when we remove such information structures from the analysis.[24] Our results also don't seem consistent with suspense/surprise preferences, a'la Ely, Frankel & Kamenica (2015): we find no evidence that ranking or valuation of information structures can be explained by the amount of suspense or surprise they

[23] Although this seems unlikely given that, by definition, all information structures increase expected likelihood of winning the prize.

[24] However, as seen in Online Appendix F Table 20, removing these information structures can influence the degree to which informativeness impacts demand for information controlling for instrumental value. This suggests that some subjects might indeed particularly dislike information structures generating maximally uncertain signals. Our experiment is not designed to identify the relative magnitude of these effects, and this may be difficult in general because increasing informativeness without increasing instrumental value necessarily involves changing the distribution of induced posterior beliefs to move closer to extremes of 0.5 and 0 or 1 (as observed in the example of Figure 9).

generate when we control for their instrumental value. Likewise, the results don't seem to be driven by preferences over the skewness of information provided by our information structures: although there is some suggestion in our data (as in some prior experiments like Masatlioglu, Orhun & Raymond (2023)) that subjects could be drawn to positively skewed structures, controlling for this does not change our findings on informativeness attitudes. Mechanisms like motivated attention and dissonance avoidance (Festinger 1957) likewise can't account for our findings. Curiosity preferences as in Golman & Loewenstein (2018) and Golman, Loewenstein, Molnar & Saccardo (2022) predict informativeness loving behavior that goes in the opposite direction of our main findings.

Our No Uncertainty treatment allows us to assess the relevance of preference-based mechanisms for our results in a more comprehensive way. In this treatment, instead of paying subjects based on their guess for a randomly drawn ball, we paid them based on the accuracy of their guesses for *all* ten balls. That is, subjects were told that all ten balls would be selected, but guesses needed to be the same for all balls in the same cell of a partition associated with an "information" structure. Thus, the objective (and certain) value of each "information" structure in this treatment is exactly equal to the instrumental value of that information structure. Furthermore, information processing required for guesses and evaluation of each "information" structure in this treatment is very similar to that required in the other two treatments. But (i) since guesses are known to apply to all balls, there is no actual information provided to subjects in the experiment and (ii) there is no objective uncertainty anywhere in the experiment. Because of (i), preferences related to the timing of information cannot apply in this treatment. Because of (ii) there is likewise no scope for explanations related to risk preferences since there is no uncertainty in these tasks. In Online Appendix C we show that the No Uncertainty treatment produces broadly similar results to our Baseline treatment. We continue to find that subjects display an aversion to "informativeness" controlling for value even though there is no actual learning occurring about an unknown state in this task.[25] This suggests that preferences for timing or risk likely are not a primary driver of our findings.

Result 5. *Our results are not consistent with recent findings (from settings where information has no instrumental value) on preferences for the timing of resolution of uncertainty. Similar patterns are observed when uncertainty is removed from the task, suggesting that our results are not an*

[25] As documented in Online Appendix C, behavior (particularly WTP) is more noisy in this treatment, likely attenuating the effect we find clearly in the Ranking data. This noise might be driven by the somewhat unnatural framing of the problem relative to the other two treatments. Probably due to this attenuation, the WTP data in aggregate does not display aversion to informativeness controlling for instrumental value. However, there is evidence suggestive of this pattern when we restrict analysis to WTP data that is ordinally consistent with ranking data.

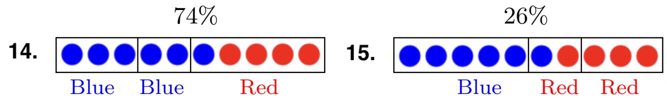


Figure 10: Example of Aversion to Informativeness with Information on Signal-Contingent Guesses
Notes: The percentage of subjects who rank an information structure as more preferred to the other is displayed above the information structure. Text below cells of the partition represent the signal-contingent guesses made in an identical problem earlier. We restrict attention to subjects in the Reverse treatment whose guesses with the two information structures are same for each ball (as seen above).

outgrowth of risk or timing preferences.

5.2 Biases and Mistakes

A second natural class of explanations for aversion to informativeness is that it derives from mistakes in how people make use of information.

First, subject might make mistakes in interpreting and optimally making use of information, and reveal these mistakes when valuing information structures. There is, after all, a great deal of evidence in the prior literature that subjects suffer from a range of judgement errors when evaluating signals in standard prior-signal updating tasks, including for example, over- and under-inference, confirmation bias and motivated reasoning. Thus, one natural hypothesis is that subjects suffer from one or more of these biases when assessing the information contained in information structures, leading them to fail to properly value them in ways that spuriously resemble distaste for informativeness.

We can rule out such mistakes by studying behavior in the Guessing section of the experiment which was specifically designed to evaluate this hypothesis. As we detail in Section 4.1 above, subjects show no evidence of systematic biases in interpreting signals from information structures, and in fact show little evidence of noise either. Indeed, our subjects make nearly perfect use of information structures to inform Guessing behavior: 98% of Guessing choices are optimal (expected earnings maximizing) in our dataset and the vast majority of our subjects *always* make optimal use of information. This strongly suggests that subjects are overwhelmingly capable of understanding how to use the information contained in information structures to inform choice.

A more subtle version of the same class of explanation is that, although subjects are capable of interpreting each piece of information they receive from information structures, they fail to properly account for this from an ex-ante perspective when valuing and comparing unfamiliar information structures before they receive information. Perhaps subjects can make optimal use of information, but fail to foresee how they will do so ex ante when evaluating information structures. There is now a growing literature showing that subjects often neglect to "unfold" decision trees, failing to contingently reason about events in the future (Esponda & Vespa 2014, Martinez-Marquina, Niederle & Vespa 2019). Perhaps subjects make a similar error here and fail to accurately think through the payoff-relevant consequences (i.e., guesses induced by each signal) of receiving information from each information structure producing an apparent aversion to informativeness.

To test this kind of explanation, we ran the Reverse treatment, which has subjects make guesses for all signals under all 16 information structures *before* they are asked to value them. The purpose of this treatment was to minimize the scope for this kind of error by giving subjects a precise sense of how each information structure impacts choice. To further strengthen the effect of this treatment, we also reminded subjects of the guesses they made (contingent on every signal) in these previous guessing tasks on their elicitation screens, allowing subjects to recall their prior engagement with each information structure. To provide a concrete example of how subjects experienced this treatment, Figure 10 displays how a subject might have seen information structures 14 and 15 (the example from Figure 9).[26] In particular, subjects are shown their signal-contingent guess of the state (red or blue) underneath each possible signal when evaluating the structure. Under the hypothesis that our main findings are driven by subjects' failure to contingently reason about how different signals induce different guesses, we would expect this treatment to eliminate or at least reduce the severity of our results. Instead, in Online Appendix B, we show that the Reverse treatment has no effect on our results at all. Even among these subjects, we find a strong preference for less informativeness.

Result 6. *Auxiliary tasks and a diagnostic treatment suggest that failures in optimal use of information or failures in foreseeing how signals will induce guesses cannot explain why demand for information is decreasing in informativeness when we control for instrumental value.*

5.3 Valuation Complexity

A third possibility is that subjects attach less value to informative structures, because these structures are more costly and difficult (i.e., more complex) to evaluate. Properly valuing an information structure, after all, requires the decision maker to aggregate a number of pieces of information about the structure: she has to consider each of the signals that could be realized, determine the optimal

[26]Figure 10 displays how these information structures were presented to a subset of the subjects (50%) in the Reverse treatment for whom induced guesses (for each ball in the set of ten) is exactly the same for the two information structures.

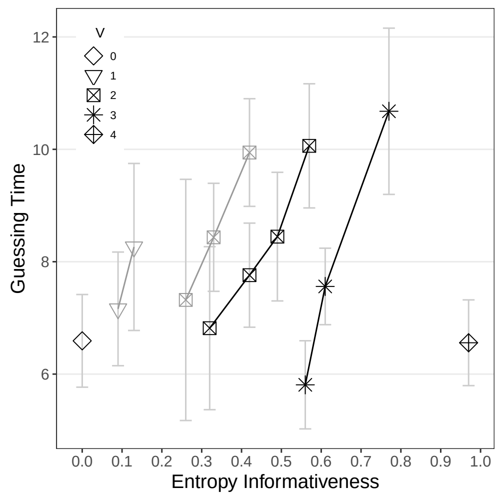


Figure 11: Cost of Informativeness: Guessing Time *Notes: Figure depicts average guessing time spent on each of the 16 information structures that are arranged by value and entropy informativeness. The information structures where the blue and red balls are not displayed in order are depicted in gray rather than black. Vertical lines denote 95 percent confidence intervals.*

action and compute payoff consequence for each case, and then aggregate over all of these possibilities. There are strong ex ante reason to think there is more information to aggregate in more informative relative to less informative structures. In particular, more informative information structures tend to have more signals, tend to generate more distinct posteriors and tend to include more extreme posteriors, all of which plausibly make the aggregation problem more difficult. Indeed, such aggregation costs have been shown to severely impact valuations in the domain of risk (Enke & Graeber 2023, Oprea 2023) and intertemporal choice (Enke, Graeber & Oprea 2023) in recent work, implicating them in some of the most famous anomalies in behavioral economics such as probability weighting and hyperbolic discounting. Could aggregation difficulties be similarly driving anomalous valuations here?

Our data and design provide several strands of evidence that seem to directly support the idea that aggregation costs of this sort drive subjects' apparent distaste for informativeness.

First, our data produces direct evidence that evaluating more informative structures requires more effort for subjects. In particular, controlling for instrumental value, subjects spend more time making signal-by-signal decisions in Guessing tasks involving more informative information structures. Figure 11 shows clear evidence that guessing time—the number of seconds it takes subjects to make guesses conditional on each possible signal realization from an information structure— increases with informativeness. For example, among the non-disordered information structures that have an instrumental value of 2 (the largest class in our design), the average time it takes subjects to make the full set of signal-contingent guesses is 47% percent higher (p-value<0.001) with the highest entropy informative information structure than with the lowest entropy informative structure.[27] Decision time ("runtime") is the most commonly used metric of complexity (information processing costs) in computer science, supporting the hypothesis that more informative structures are more complex to evaluate.[28]

Second, our finding of distaste for informativeness remains even after we remove uncertainty from the task in our No Uncertainty treatment. With risk and timing removed, the only possible reason to fail to maximize value in this problem is the difficulty of properly valuing the descriptive components of the information structure. Indeed, arguably the only substantive connection between the Baseline treatment and the No Uncertainty treatment is the similar cognitive processing required to evaluate the structure. Broadly similar aversion to informativeness in the two settings therefore seems to suggest that this shared cognitive burden is the driver of this result.

Third, the evident difficulty of valuing more informative structures, seems to be rooted in the costs of aggregating its components and not in other costs in the choice problem. In particular (as already discussed) our design rules out the hypothesis that valuation difficulties stem from difficulties in assessing signal-contingent choices: having subjects make these choices ahead of time, and showing them to subjects directly during valuation (as we do in the Reverse treatment) has no impact on measured informativeness aversion. The only other possibility would seem to be that the difficulty (cognitive costs) of optimally *using* information is higher for more informative structures, and that subjects anticipate this difficulty when valuing those structures. However, this hypothesis doesn't bear scrutiny. To decide how to optimally respond to a signal in our experiment, a subject simply needs to identify whether there are more red or blue balls in a single partition subset clearly indicated by the experimental software. This is identically true for all signals and all information structures. If anything, we might expect this task to be somewhat *easier* for more informative structures since partition subsets (signals) tend to contain fewer balls in these structures. This seems to leave only the difficulty of aggregation itself as the source of the difficulty of evaluating information structures.

Why do informativeness-driven aggregation difficulties lead to a systematic aversion to informativeness? The most likely explanation is that decision makers tend to economize on the costs

[27] The same pattern in also observed in the Reverse and No Uncertainty treatments.

[28] The use of decision time as a metric of complexity is controversial in the literature, because subjects may choose not to expend effort at all on particularly difficult tasks. This will produce a non-monotonic relationship between complexity and decision time. This is arguably not a concern in our data since we have clear evidence that subjects virtually never "give up" – almost all subjects make rational choices in our Guessing tasks.

of precisely calculating instrumental value by imprecisely estimating value instead – and do so increasingly as information structures grow more informative and the aggregation task grows more burdensome. Subjects respond to the imperfect or incomplete understanding of value that results from this decision by cautiously under-valuing informative structures, shading their valuations towards the experiment's default of no information.[29] This kind of cautious attenuation has recently been formalized by "noisy coding" models (Woodford 2020) which have been empirically successful, accounting for a wide range of anomalous behaviors including small stakes risk aversion (Khaw, Li & Woodford 2021), probability weighting (Enke & Graeber 2023, Vieider 2023, Frydman & Jin 2023), Bayesian reasoning failures (Ba, Bohren & Imas 2023) and hyperbolic discounting (Gabaix & Laibson 2022, Vieider 2021, Enke, Graeber & Oprea 2023).[30]

Result 7. *More informative structures require more cognitive effort to evaluate. This and several other strands of evidence suggest that distaste for informativeness is driven by information processing costs of valuing structures, which increase in their informativeness.*

6 Discussion

In standard economic theory informativeness influences information demand only to the extent that it produces instrumental value – i.e., to the extent that it is expected to improve decision making in relevant decision tasks. The results reported in this paper suggest that this is not the case: informativeness has an independent, first order influence on information demand. In particular, demand for information sharply decreases in informativeness, conditional on instrumental value. We find that this aversion to informativeness is often severe enough to make subjects prefer less instrumentally valuable information to more valuable alternatives, leading them to leave earnings "on the table."

Additional evidence from our experiment suggest that this aversion to informativeness arises because informative structures are more 'complex' (i.e. more costly or difficult to evaluate), leading subjects to undervalue them. Our design allows us to rule out several alternative explanations for this pattern: they cannot be (i) rationalized as an outgrowth of subjects' preferences for the timing of information, (ii) driven by mistakes in optimal use of information; (iii) arise from failures to reason about information-contingent actions.

[29] In our elicitations, especially our WTP elicitations receiving no information is quite literally the default outcome that the subject is paying to avoid

[30] An alternative possibility is that subjects simply have a primitive distaste for complex information structures (independent of difficulties in evaluating them) that leads them to undervalue them. This seems less plausible to us, but is also consistent with our data.

These results suggest that even in the simplest possible settings (e.g., our experiment), decision makers face a difficult aggregation problem when evaluating information structures: they have to consider and weigh all possible signal realizations, determine the optimal action and compute payoff consequence for each case, and then aggregate over all these possibilities, condensing this information into a value. The costs and difficulties of doing this correctly rise with the informativeness of the structure, meaning the distortions it produces follow a predictable pattern that can be used in modeling and information design.

Indeed, our results have policy implications on how information should be provided to decision makers to most effectively influence behavior. Our results suggest especially that information should be narrowly targeted to the decision problem the information is meant to inform. Extraneous or irrelevant information is likely to be treated as an economic bad in the market for information and makes information less effective as a policy instrument. Even in contexts (such as that of our experiment) in which decision makers are able to easily make optimal use of the signals informative structures produce, they nonetheless should be expected to undervalue and avoid such structures because of the costs of evaluating their value, ex ante.

These findings reveal a connection between information demand and a growing number of contexts in which complexity of valuation (which typically involves aggregating different pieces of information) has been shown to produce first order distortions in choice. For instance, the difficulty of correctly valuing an information structure is formally similar to the problem of evaluating a compound lottery, which decision makers have well-documented difficulties with (Halevy 2007, Chew, Miao & Zhong 2017). Similarly, recent research suggests that the complexity of aggregation is a key driver of classical anomalies in risky choice, such as probability weighting (Enke & Graeber 2023, Oprea 2023) and classical anomalies in intertemporal choice, such as hyperbolic discounting (Enke, Graeber & Oprea 2023). Thus our findings suggest a parsimonious connection between anomalies in information demand and anomalies in a number of other canonical choice settings in economics.

Much of what we know about information demand so far comes from settings in which information has no instrumental value. A key methodological lesson from our experiment is that behavior in such settings is likely shaped by a very different reasoning process and hence influenced by different characteristics of information structures than settings in which information is required to inform choice. In particular, previous literature (as discussed in 5.1) often documents information loving behavior when information has no instrumental value. Our results, which go in the opposite direction, suggest that the aversion to informativeness documented in our paper is a byproduct of the difficulty decision makers encounter in assessing the instrumental value of an information structure – a problem that is lifted in non-instrumental settings. For this reason, our results suggest that we cannot easily counterfactually project findings from non-instrumental settings to instrumental settings (or vice versa).

Finally, our results provide a new kind of evidence in support of the central trade-off at the heart of rational inattention models, one of the most influential and often used formal theories of bounded rationality. In these models, people acquire information to maximize utility but suffer information costs that influence this choice (Sims 2003, Matějka & McKay 2015, Caplin & Dean 2013). Our paper contributes to this literature by expanding our understanding of when and why agents act as if information is costly. We show that these information costs need not be limited to costs associated with generating this information or making use of this information, but can also arise due to the cognitive effort required to *evaluate* the ex-ante value of information. Our results therefore suggest that rational inattention models may also be effective models of complexity (information processing) aversion, and may therefore have a much wider scope of application than is typically supposed.

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Online Appendix for

Too Much Information

Menglong Guan   Ryan Oprea   Sevgi Yuksel

CONTENTS:

A. Optimal WTP for an Information Structure

B. Varying the order of Guesses versus Elicitation of Demand for Information

C. The No Uncertainty Treatment

D. Further Analysis on Clusters

E. Characteristics of Information Structures

F. Additional Plots and Tables

G. Screenshots and Instructions for Baseline Treatment

A Optimal WTP for an Information Structure

The goal of this section is to study how WTP for an information structure changes with risk preferences. Given the CRRA (constant relative risk aversion) utility function

$$u(x) = \begin{cases} \dfrac{x^{1-r}-1}{1-r}, & \text{if } r \neq 1 \\ log(x), & \text{if } r = 1 \end{cases}$$

in which r is the coefficient of relative risk aversion, we consider a relatively wide range of $r \in [-1, 3]$ and compute the optimal WTPs for information structures with value V (as defined in equation 2).[31,32]

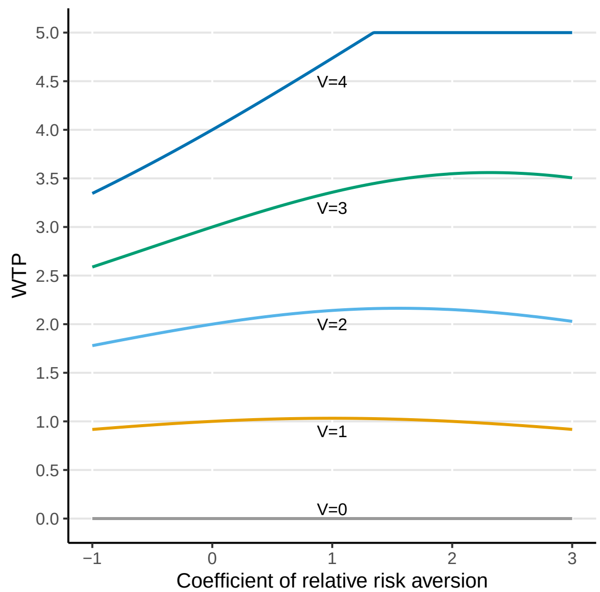


Figure 12: Optimal WTP for Information Structures under CRRA Utility *Notes: The optimal WTP of a risk neutral agent is V, that is, the WTP at the risk aversion coefficient being 0 in the figure. Given the budget of \$5, theoretical WTPs (for the information structure with $V = 4$) that are higher than 5 are recorded as 5.*

[31]Gandelman & Hernández-Murillo (2015) estimate the coefficient of relative risk aversion of 75 countries and find the values are between 0 to 3. We add the range [-1,0] so to take into account risk loving behavior as well.

[32]The optimal WTP is solved by finding out y that makes $pu(22) + (1-p)u(12) = p^s u(22-y) + (1-p^s)u(12-y)$, where p and p^s are guessing accuracies without or with information, respectively. Note that a subject who guesses correctly (incorrectly) and pays \$y for an information structure receives \$$22-y$ (\$$12-y$) at the end of the experiment.

B Varying the order of Guess versus Elicitation of Demand for Information

B.1 Baseline Treatment

Table 3: Determinants of Demand for Information (Elicitation of Demand First)

	Ranking (Logit)			**Difference in WTP (OLS)**			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
Difference in Value	0.880***		1.678***	0.565***		0.975***	1.289***
	(0.075)		(0.183)	(0.056)		(0.119)	(0.110)
Difference in Informativeness		2.710***	-3.395***		1.954***	-1.766***	-2.400***
		(0.219)	(0.587)		(0.204)	(0.386)	(0.390)
Difference in Disorder	-0.304***	-0.155*	-0.658***	0.057	0.182**	-0.124*	-0.242***
	(0.087)	(0.081)	(0.105)	(0.066)	(0.071)	(0.075)	(0.077)
Clusters	109	109	109	109	109	109	108

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. OLS regression (4) includes only pairwise comparisons in which WTP data is ordinally consistent with Ranking data. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

B.2 Reverse Treatment

Table 4: Determinants of Demand for Information (Elicitation of Guesses First)

	Ranking (Logit)			**Difference in WTP (OLS)**			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
Difference in Value	0.658***		1.486***	0.448***		0.823***	1.169***
	(0.111)		(0.262)	(0.082)		(0.204)	(0.210)
Difference in Informativeness		1.981***	-3.528***		1.525***	-1.615**	-2.378***
		(0.358)	(0.881)		(0.287)	(0.663)	(0.691)
Difference in Disorder	-0.340***	-0.245**	-0.711***	0.002	0.095	-0.164	-0.315**
	(0.129)	(0.123)	(0.163)	(0.095)	(0.096)	(0.120)	(0.133)
Clusters	54	54	54	54	54	54	54

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. OLS regression (4) includes only pairwise comparisons in which WTP data is ordinally consistent with Ranking data. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

C The No Uncertainty Treatment

Table 5: Determinants of Demand for Information (No Uncertainty)

	Ranking (Logit)			**Difference in WTP (OLS)**			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
Difference in Value	0.735***		1.143***	0.387***		0.362***	0.704***
	(0.109)		(0.206)	(0.069)		(0.134)	(0.134)
Difference in Informativeness		2.478***	-1.759**		1.489***	0.106	-0.760*
		(0.381)	(0.719)		(0.251)	(0.399)	(0.422)
Difference in Disorder	-0.541***	-0.368***	-0.725***	-0.033	0.092	-0.022	-0.244**
	(0.094)	(0.088)	(0.111)	(0.085)	(0.091)	(0.107)	(0.100)
Clusters	61	61	61	61	61	61	61

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. OLS regression (4) includes only pairwise comparisons in which WTP data is ordinally consistent with Ranking data. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

D Further Analysis on Clusters

D.1 Comparison of Clusters

Table 6: Optimality of Guesses and Demand by Cluster

	Share	Opt. of Guesses	Opt. of Demand (Rank)	Opt. of Demand (WTP)
Cluster 1	45	99	85	63
Cluster 2	25	99	89	61
Cluster 3	21	98	64	48
Cluster 4	9	94	36	42

Notes: Numbers denote percentages. Here we focus on cases with strict value difference. Demand is coded as optimal given WTP data if subjects pay more (by more than 10 cents) for the more optimal information structure.

D.2 Analysis on the Largest Three Clusters

Table 7: Determinants of Demand for Information (Cluster 1)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	1.292***		3.744***	0.686***		1.425***
	(0.066)		(0.164)	(0.065)		(0.162)
Difference in Informativeness		3.099***	-9.855***		2.252***	-3.189***
		(0.182)	(0.638)		(0.229)	(0.523)
Difference in Disorder	-0.266***	-0.194**	-1.328***	0.053	0.173**	-0.275***
	(0.096)	(0.082)	(0.132)	(0.077)	(0.084)	(0.097)
Clusters	74	74	74	74	74	74

*Notes: Only Cluster 1 (45% of the subjects) are included. Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 8: Determinants of Demand for Information (Cluster 2)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	1.454***		0.809***	0.514***		0.548***
	(0.136)		(0.182)	(0.093)		(0.115)
Difference in Informativeness		5.855***	2.942***		1.945***	-0.148
		(0.538)	(0.755)		(0.372)	(0.439)
Difference in Disorder	-1.123***	-0.606***	-0.837***	-0.090	0.067	-0.105
	(0.158)	(0.165)	(0.171)	(0.118)	(0.118)	(0.115)
Clusters	40	40	40	40	40	40

*Notes: Only Cluster 2 (25% of the subjects) are included. Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 9: Determinants of Demand for Information (Cluster 3)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	0.421***		1.085***	0.309***		0.617**
	(0.059)		(0.170)	(0.090)		(0.237)
Difference in Informativeness		1.237***	-2.843***		1.025***	-1.332*
		(0.213)	(0.651)		(0.311)	(0.786)
Difference in Disorder	-0.081	-0.039	-0.374**	0.041	0.098	-0.096
	(0.156)	(0.161)	(0.167)	(0.119)	(0.124)	(0.136)
Clusters	35	35	35	35	35	35

*Notes: Only Cluster 3 (21% of the subjects) are included. Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

D.3 Analysis on the Smallest Cluster

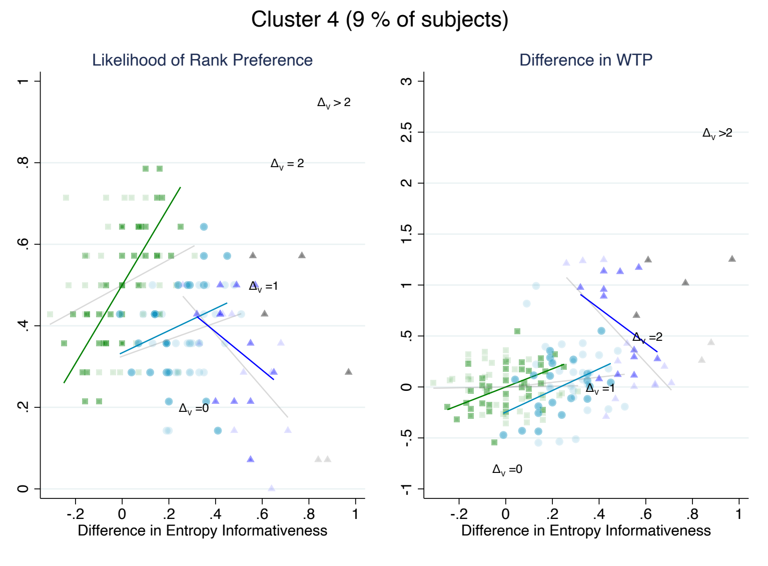


Figure 14: Preference for Information by Value and Informativeness (Cluster 4) *Notes: Each dot denotes a pair of information structures. Green squares denote pairs where both information structures are of the same value. Blue dots denote pairs where the value difference between the first and second information structure is 1. The darker blue (gray) triangles denote pairs where the value difference is equal to (larger than) 2. To account for the potential impact of visual complexity, pairs with at least one information structure where the blue and red balls are not displayed in order are depicted in a lighter color. Gray lines depict the best linear fits for each of the first three categories. Darker lines in the corresponding colors denote the best linear fits where the pairs depicted in a lighter color are not included.*

Table 10: Determinants of Demand for Information (Cluster 4)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	-0.309**		-0.633	0.264		0.117
	(0.146)		(0.459)	(0.180)		(0.339)
Difference in Informativeness		-1.005*	1.397		1.080	0.632
		(0.528)	(1.725)		(0.642)	(0.919)
Difference in Disorder	0.349	0.292	0.493	0.326*	0.428**	0.391*
	(0.295)	(0.322)	(0.372)	(0.180)	(0.194)	(0.215)
Clusters	14	14	14	14	14	14

*Notes: Only Cluster 4 (9% of the subjects) are included. Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

D.4 Alternative Clustering method: K-Modes

Table 11: Determinants of Demand for Information (By K-Modes Cluster)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	C1	C2	C3	C1	C2	C3
Difference in Value	2.746***	0.956***	2.591***	1.254***	0.567***	1.115***
	(0.217)	(0.169)	(0.310)	(0.157)	(0.112)	(0.305)
Difference in Informativeness	-7.337***	1.670***	-8.109***	-2.655***	-0.212	-2.981***
	(0.633)	(0.564)	(1.071)	(0.469)	(0.401)	(1.035)
Difference in Disorder	-1.394***	-0.664***	-0.385**	-0.288**	0.004	-0.126
	(0.137)	(0.132)	(0.193)	(0.110)	(0.098)	(0.144)
Clusters	64	54	35	64	54	35

*Notes: C1, C2 and C3 refer to Clusters 1, 2, and 3 under the K-Modes clustering and represent 39%, 33%, and 21% of the data, respectively. Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. ***1%, **5%, *10% significance.*

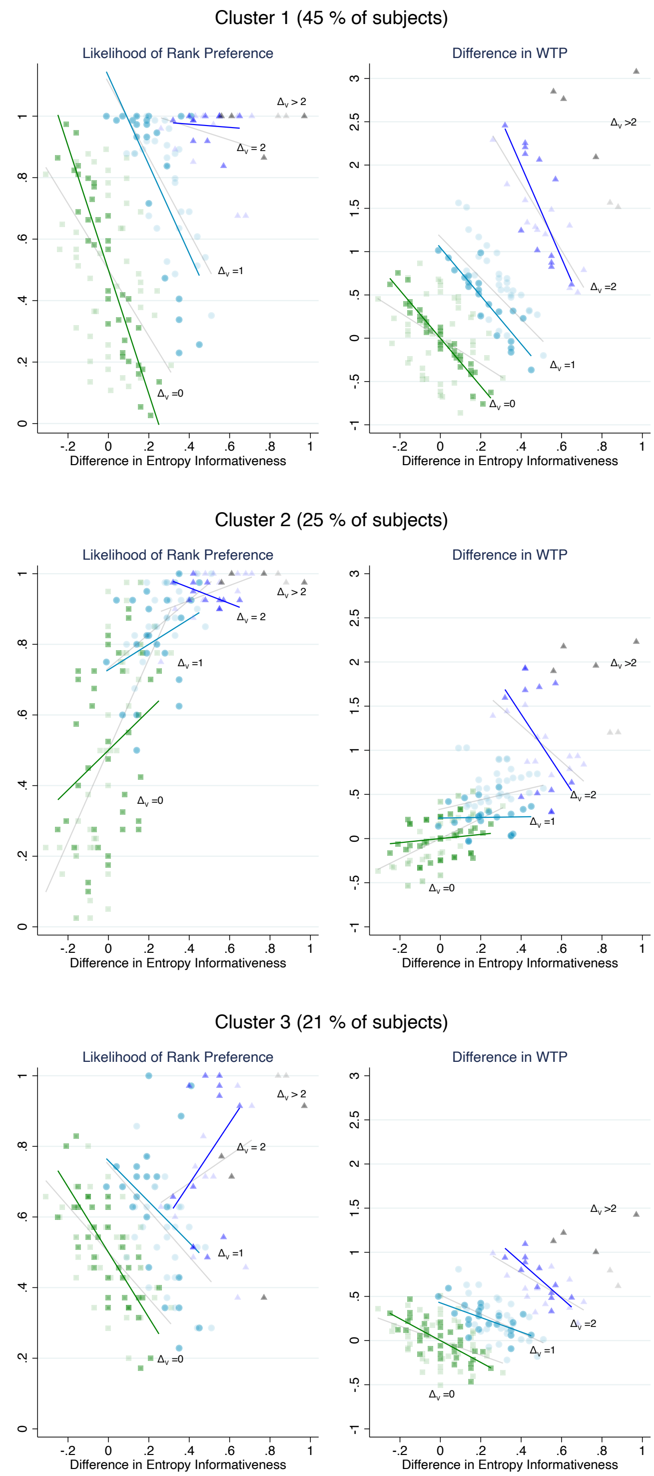


Figure 13: Preference for Information Structure by Value and Informativeness Separated by Cluster *Notes: Each dot denotes a pair of information structures. Green squares denote pairs where both information structures are of the same value. Blue dots denote pairs where the value difference between the first and second information structure is 1. The darker blue (gray) triangles denote pairs where the value difference is equal to (larger than) 2. To account for the potential impact of visual complexity, pairs with at least one information structure where the blue and red balls are not displayed in order are depicted in a lighter color. Gray lines depict the best linear fits for each of the first three categories. Darker lines in the corresponding colors denote the best linear fits where the pairs depicted in a lighter color are not included.*

E Characteristics of Information Structures

Table 12: Characteristics of Information Structures

Information	value	informativeness	disorder	varpost	nsignal	ndistinctpost	uncertain	certain	skewness
1	0	0	0	0	1	1	0	0	
2	1	0.09	1	0.03	2	2	0	0	-0.873
3	1	0.13	1	0.04	2	2	0	0	0
4	2	0.26	1	0.082	2	2	0	0	-0.408
5	2	0.32	0	0.09	2	2	0	0.2	-1.5
6	2	0.33	1	0.093	3	3	0	0.2	-1.372
7	2	0.42	0	0.107	2	2	0	0.4	0.408
8	2	0.42	1	0.107	4	3	0	0.4	-0.868
9	2	0.42	0	0.107	3	3	0	0.4	-0.868
10	2	0.42	0	0.107	3	2	0	0.4	0.408
11	2	0.49	0	0.12	3	3	0	0.5	-0.577
12	2	0.57	0	0.14	3	3	0.4	0.6	-0.344
13	3	0.56	0	0.154	2	2	0	0.3	-0.873
14	3	0.61	0	0.16	3	2	0	0.5	0
15	3	0.77	0	0.19	3	3	0.2	0.8	-0.398
16	4	0.97	0	0.24	2	2	0	1	-0.408

Notes: Information denotes the information structures shown in Figure 2; value is instrumental value as defined in equation 2; informativeness is entropy informativeness as defined in equation 1; disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls are presented out of order; varpost denotes the variance of $P(b|s)$, i.e., the variance of Bayesian posterior of the drawn ball being blue given signal s; nsignal denotes the number of distinct signals that an information structure can generate; ndistinctpost denotes the number of distinct posteriors that an information structure can induce; uncertain denotes the probability of generating maximally certain signals (i.e., signals induce posterior of 1 or 0); certain denotes the probability of generating maximally uncertain signals (i.e., signals induce posterior of 0.5); skewness denotes the third normalized moment of Bayesian posterior $P(b|s)$.

Table 13: Blackwell Ordering

Information	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
2	0		-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
3		0	-1		-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
4			0								-1	-1	-1	-1	-1
5				0	-1		-1	-1		-1	-1	-1		-1	-1
6					0		-1	-1		-1	-1	-1		-1	-1
7						0			0		-1		-1	-1	-1
8							0	0		-1	-1			-1	-1
9								0		-1	-1			-1	-1
10									0		-1		-1	-1	-1
11										0	-1			-1	-1
12											0			-1	-1
13												0		-1	-1
14													0	-1	-1
15														0	-1
16															0

Notes: Information denotes the information structures shown in Figure 2. The Blackwell ordering takes values 1, 0, -1 when the row information structure is more, equally or less Blackwell informative than the column one. The value is missing if Blackwell comparison cannot be made.

Table 14: Determinants of Demand for Information (Ranking)

	Ranking (Logit)					
	(1)	(2)	(3)	(4)	(5)	(6)
Difference in Value	1.607***	1.210***	1.532***	1.367***	1.674***	1.107***
	(0.150)	(0.137)	(0.144)	(0.136)	(0.150)	(0.126)
Difference in Informativeness	-3.436***	-1.577***	-3.000***	-2.142***	-3.896***	-1.064**
	(0.487)	(0.478)	(0.451)	(0.441)	(0.473)	(0.474)
Difference in Disorder	-0.677***	-0.589***	-0.615***	-0.488***	-0.674***	-0.422***
	(0.088)	(0.086)	(0.090)	(0.087)	(0.089)	(0.087)
Difference in Uncertain		-0.624***				-0.544***
		(0.096)				(0.101)
Difference in # Signals			-0.129**			0.018
			(0.055)			(0.062)
Difference in # Distinct Posteriors				-0.326***		-0.312***
				(0.066)		(0.075)
Difference in Certain					0.102**	0.098***
					(0.046)	(0.035)
Clusters	163	163	163	163	163	163

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Descriptions of the other characteristic measures can be found in Table 12. Except for Value and Informativeness, the other differences in characteristic measures are defined as follows: 1 if the first information structure has a higher characteristic measure than the other in a pairwise comparison, -1 if the opposite, and 0 otherwise. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 15: Determinants of Demand for Information (WTP)

	Difference in WTP (OLS)					
	(1)	(2)	(3)	(4)	(5)	(6)
Difference in Value	0.924***	0.951***	0.987***	1.027***	0.999***	1.067***
	(0.104)	(0.105)	(0.104)	(0.106)	(0.105)	(0.110)
Difference in Informativeness	-1.716***	-1.840***	-2.103***	-2.282***	-2.246***	-2.591***
	(0.338)	(0.355)	(0.337)	(0.353)	(0.346)	(0.402)
Difference in Disorder	-0.137**	-0.143**	-0.197***	-0.229***	-0.132**	-0.216***
	(0.064)	(0.062)	(0.062)	(0.062)	(0.064)	(0.062)
Difference in Uncertain		0.043				0.007
		(0.060)				(0.057)
Difference in # Signals			0.128***			0.046
			(0.045)			(0.039)
Difference in # Distinct Posteriors				0.155***		0.102**
				(0.053)		(0.048)
Difference in Certain					0.128***	0.083***
					(0.027)	(0.013)
Clusters	163	163	163	163	163	163

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Descriptions of the other characteristic measures can be found in Table 12. Except for Value and Informativeness, the other differences in characteristic measures are defined as follows: 1 if the first information structure has a higher characteristic measure than the other in a pairwise comparison, -1 if the opposite, and 0 otherwise. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

F Additional Plots and Tables

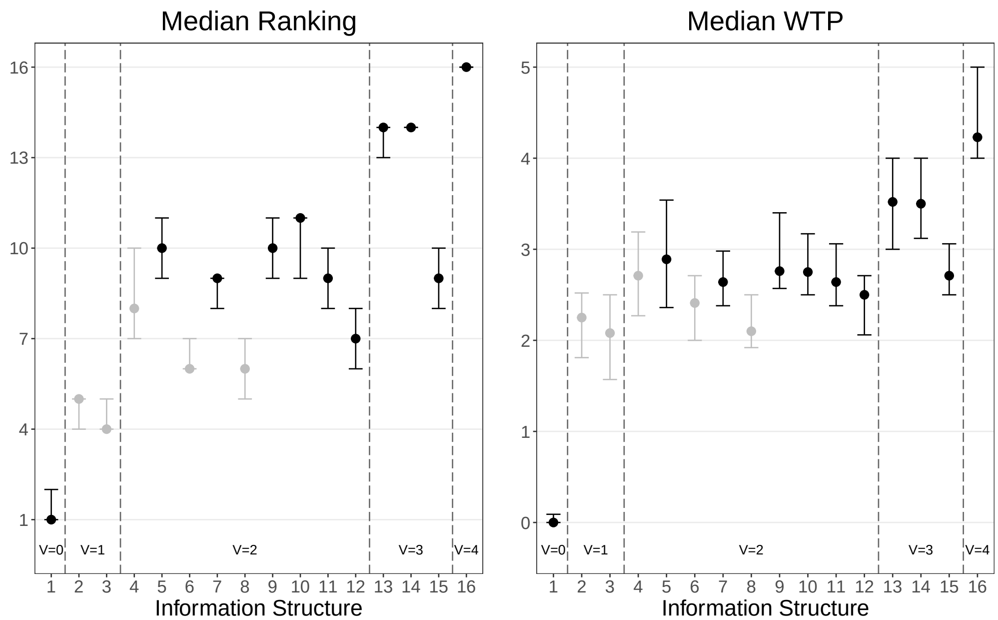
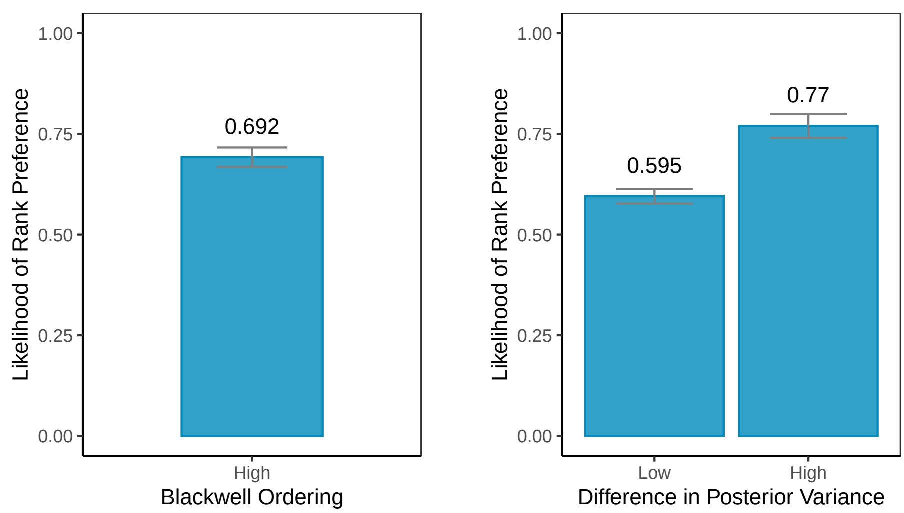


Figure 15: Median Rank and WTP by Information Structure *Notes: Information structures are the ones as shown in Figure 2. V denotes the instrumental value of an information structure as defined in equation 2. Vertical lines are 95 percent confidence intervals that are derived from the exact sign test.*



(a) (b)

Figure 16: Demand for Information by Blackwell Ordering and Posterior Variance *Notes: The figures condition on all pairwise comparisons between information structures where there there is a strict positive difference—on Blackwell Ordering for (a) or variance of posterior for (b)—between the first and the second structure. The bars depict the likelihood with which the first structure was ranked as more preferred to the second. In (a),* High *represents the first structure is strictly more Blackwell informative. In (b),* Low *(*High*) represents all pairwise comparisons where the difference is weakly lower (strictly higher) than the median difference of variance of posterior (i.e., 0.0635).*

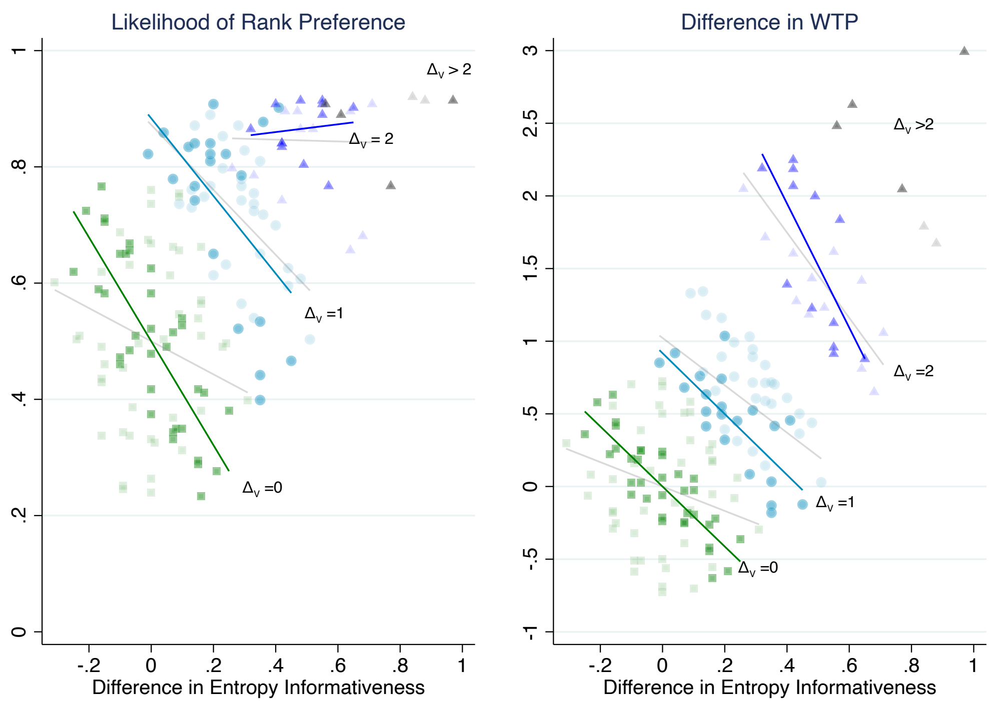


Figure 17: Preference for Information Structure by Value and Informativeness *Notes: This is the same as Figure 8 except that pairwise comparisons with WTPs ranked inconsistently with the Ranking data are dropped in the right panel.*

Table 16: Determinants of Demand for Information

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	0.800***		1.607***	0.527***		0.924***
	(0.063)		(0.150)	(0.046)		(0.104)
Difference in Informativeness		2.453***	-3.436***		1.812***	-1.716***
		(0.193)	(0.487)		(0.167)	(0.338)
Difference in Disorder	-0.317***	-0.186***	-0.677***	0.039	0.153***	-0.137**
	(0.072)	(0.067)	(0.088)	(0.054)	(0.057)	(0.064)
Clusters	163	163	163	163	163	163

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) are in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 17: Determinants of Demand for Information (By Value Difference)

	Ranking (Logit)				Difference in WTP (OLS)			
	$\Delta V = 0$	$\Delta V = 1$	$\Delta V = 2$	$\Delta V > 2$	$\Delta V = 0$	$\Delta V = 1$	$\Delta V = 2$	$\Delta V > 2$
Difference in Informativeness	-4.638***	-4.023***	-0.959**	-0.210	-1.845***	-1.543***	-2.541***	0.443**
	(0.573)	(0.536)	(0.468)	(0.395)	(0.400)	(0.363)	(0.391)	(0.200)
Difference in Disorder	-0.876***	-0.494***	-0.234**	-0.534**	-0.368***	-0.169***	0.064	0.961***
	(0.103)	(0.086)	(0.111)	(0.233)	(0.071)	(0.064)	(0.069)	(0.139)
Constant	0.178***	1.876***	2.123***	2.051***	0.048**	0.761***	2.366***	1.755***
	(0.051)	(0.166)	(0.281)	(0.353)	(0.019)	(0.105)	(0.241)	(0.202)
Clusters	163	163	163	163	163	163	163	163

*Notes: ΔV denotes the value (as defined in equation 2) difference between two structures in a pairwise comparison. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 18: Determinants of Demand for Information (Value and Blackwell)

	Ranking (Logit)			Difference in WTP (OLS)		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	0.800***		0.904***	0.527***		0.612***
	(0.063)		(0.080)	(0.046)		(0.055)
Blackwell		0.720***	-0.256***		0.591***	-0.147***
		(0.055)	(0.066)		(0.054)	(0.037)
Difference in Disorder	-0.317***	-0.309***	-0.312***	0.039	0.072	0.079
	(0.072)	(0.065)	(0.072)	(0.054)	(0.058)	(0.058)
Clusters	163	163	163	163	163	163

*Notes: Value denotes instrumental value as defined in equation 2. Blackwell denotes whether the first structure is strictly more Blackwell informative than the other in a pairwise comparison. Details can be found in Table 13. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 19: Determinants of Demand for Information (Value and Posterior Variance)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	0.800***		1.954***	0.527***		1.104***
	(0.063)		(0.193)	(0.046)		(0.133)
Difference in Variance of $P(b\|s)$		10.833***	-19.396***		7.763***	-9.827***
		(0.840)	(2.683)		(0.702)	(1.845)
Difference in Disorder	-0.317***	-0.200***	-0.683***	0.039	0.137**	-0.145**
	(0.072)	(0.068)	(0.089)	(0.054)	(0.056)	(0.064)
Clusters	163	163	163	163	163	163

*Notes: Value denotes instrumental value as defined in equation 2. Variance of $P(b|s)$ denotes the variance of the Bayesian posterior of the drawn ball being blue given signal s. It is a valid measure of uncertainty reduction (informativeness) according to Frankel & Kamenica (2019). Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

Table 20: Determinants of Demand for Information (Removing Maximal Uncertainty)

	Ranking (Logit)			**Difference in WTP (OLS)**		
	(1)	(2)	(3)	(1)	(2)	(3)
Difference in Value	0.914***		1.281***	0.550***		0.978***
	(0.078)		(0.148)	(0.048)		(0.107)
Difference in Informativeness		3.488***	-1.636***		2.076***	-1.883***
		(0.293)	(0.498)		(0.188)	(0.360)
Difference in Disorder	-0.459***	-0.242***	-0.589***	0.013	0.131**	-0.139**
	(0.077)	(0.072)	(0.087)	(0.056)	(0.058)	(0.062)
Clusters	163	163	163	163	163	163

*Notes: Value denotes instrumental value as defined in equation 2. Informativeness denotes entropy informativeness as defined in equation 1. Disorder denotes whether an information structure has a visual disorder, i.e., whether the blue and the red balls were presented out of order. Pairwise comparisons that include either of the two information structures that may generate maximally uncertain signals (i.e., information structures 12 and 15 as shown in Figure 2) are not included. Standard errors (clustered at the subject level) in parentheses. *** 1%, ** 5%, * 10% significance.*

G Screenshots and Instructions for Baseline Treatment

The followings are screenshots of the experiment software and comprehension questions that subjects had to answer correctly to be able to begin the experiment.

Instructions

- We will start by providing you with **INSTRUCTIONS** for the study.
- We will ask you **COMPREHENSION QUESTIONS** to check that you understand the instructions. You should be able to answer all of these questions correctly.
- Please read and follow the instructions closely and carefully.
- If you **COMPLETE** the main parts of the study, you will receive a **GUARANTEED PAYMENT** of **$7.00**.
- In addition, your **CHOICES** in the **DECISIONS** portion of the study will result in **PERFORMANCE-BASED EARNINGS**. You will experience several **TASKS** worth **REAL MONEY**.
- This study consists of **3 PARTS**.
- You will be paid based on your choices in a **RANDOMLY SELECTED** part.
- Your decisions in earlier parts will have no impact on your potential earnings in later parts.

Guessing Questions

- **Overview:**
  - In this part there will be total of **16 GUESSING QUESTIONS**. In each Guessing Question we will show you 10 balls: 6 blue balls and 4 red balls.
  - Your task will be simply to **GUESS** the color of a ball randomly selected by the computer.
  - You will earn a **$10 BONUS** payment if your guess is correct and **$0** if your guess is incorrect.

- On your screen, we will present the 6 blue balls and 4 red balls arrayed like this:

- or this:

While the order of the balls might vary on the screen, there will always be 6 blue balls and 4 red balls.

- **ONE** of the balls shown on the screen will be **RANDOMLY SELECTED** by the computer. Each ball is equally likely to be selected. Your task is to **GUESS** the color of the randomly selected ball.

- You will submit your guess on the ball's color by clicking radio buttons like these.

I guess the color to be:	○ **Blue** ○ **Red**

Continue Instructions

Information

- **Overview:**
  - Before you guess the color of the selected ball, you will receive some **INFORMATION** from an **INFORMATION SOURCE** about which ball the computer selected.
  - Each information source divides the 6 blue balls and 4 red balls into different groups and informs you about *which group* the selected ball is in before you have to make a guess.
  - You will earn a **$10 BONUS** payment if your guess is correct and $0 if your guess is incorrect.

- An information source will divide the 10 balls into **GROUPS** like this:

- or like this:

(these are only examples -- we will show you many different groupings across questions)

- In these questions, we will tell you which Group the randomly selected ball is in **BEFORE** you guess the color of the ball.

- In fact, to make things easier, we will ask you for your guess for **EACH POSSIBLE** piece of information you might receive (i.e., each possible group we might tell you the ball is in).

- 

For instance, in the example above, we would ask you what your guess about the color of the ball will be if you learn the ball is in Group 1 **AND** what your guess about the color of the ball will be if you learn the ball is in Group 2 etc.

- 

Similarly, for the example above, we would ask you what your guess about the color of the ball will be if you learn the ball is in Group 1 **AND** what your guess about the color of the ball will be if you learn the ball is in Group 2.

- You will indicate your guess for each possible piece of information you might receive by filling out a table like this. Each **ROW** corresponds to a different piece of information you might receive about the selected ball (specifying which group the ball is in).

If I learn the ball is in **Group 1**, I will guess the color to be:	○ **Blue** ○ **Red**
If I learn the ball is in **Group 2**, I will guess the color to be:	○ **Blue** ○ **Red**

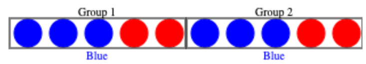
- At the end of the experiment, if one of these rounds is selected for payment, we will look at which Group the randomly selected ball is in and whether or not the color of the ball matches your guess for that Group. You will then earn $10 if your guess is correct.

- This means that you should input your best guess about the color of the ball **FOR EACH GROUP** to maximize your expected earnings!

Practice Round

There are 6 blue balls, and 4 red balls. One of these balls will be randomly selected and you earn $10 if you correctly guess the color (blue or red):

You will learn which of the following Groups the ball is in before you guess:



Please tell us what color you will guess if you learn the ball is in each of these possible Groups:

If I learn the ball is in **Group 1**, I will guess the color to be:	**Blue** **Red**
If I learn the ball is in **Group 2**, I will guess the color to be:	**Blue** **Red**

*(Remember, **if this were not a practice period** these choices would determine your actual guess and therefore your payment!)*

Practice Feedback

If the selected ball is in Group 1, your guess about the color of the ball will be CORRECT if the color is BLUE, INCORRECT if the color is RED.

If the selected ball is in Group 2, your guess about the color of the ball will be CORRECT if the color is BLUE, INCORRECT if the color is RED.

Continue

Ranking Information Sources

- **Overview:**
  - In this part, you will determine how you RANK different information sources shown to you on your screen.
  - Each information source divides the 6 blue balls and 4 red balls into different groups as shown to you earlier.
  - Your ranking (from highest to lowest) reveals which information sources you would rather receive information from before making a guess about the color of the selected ball.

- We will show you pictures of 16 different information sources in a random order.

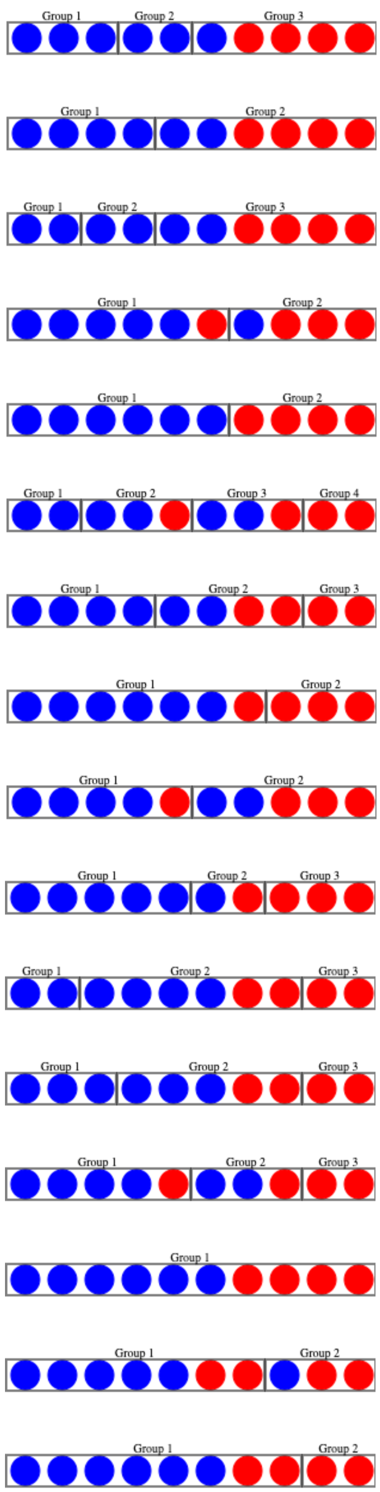
- You will use your mouse to click and drag these sources from most preferred (at the top) to least preferred (at the bottom)

- If this part is selected for payment, at the end of the experiment, the computer will randomly select two of the information sources, and you will receive information from the one that you ranked higher before you are asked to guess the color of the randomly selected ball. As in other parts, you will earn a $10 BONUS payment if your guess is correct and $0 if your guess is incorrect.

Continue Instructions

Ranking Information Sources

Please drag these information sources on the screen to rank them in order from most favorite (top of the screen) to least favorite (bottom of the screen). The computer will randomly pick two information sources, and you will receive information from the one that you ranked higher before you are asked to make a guess about the color of the randomly selected ball. As in other parts, you will earn a $10 BONUS payment if your guess is correct and $0 if your guess is incorrect.



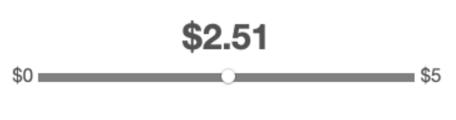
Buy Information Questions

- **Overview:**
    - In this part, you will determine how much you would be **WILLING TO PAY** for the information provided by an information source before you guess the color of the selected ball.
    - There will be 16 questions in total, one corresponding to each of the information sources you ranked in the previous part. They will be presented in the same order you ranked them.
    - If this part is selected for payment, one of the questions will be randomly selected at the end of the experiment. Your answer to that question will determine whether or not you receive information from this source before you are asked to make a guess about the color of the selected ball. As in other parts, you will earn a $10 BONUS payment if your guess is correct and $0 if your guess is incorrect

- In each of these questions, we will give you a budget of $5.

- You will then tell us the **MAXIMUM AMOUNT** you would be willing to pay (out of your budget of $5) to buy information from this source.
    - If you buy the information, you will know which group the ball is in before making your guess.
    - If you don't buy the information, you will <u>not</u> know which group the ball is in before making your guess.

- You will indicate the **MAXIMUM AMOUNT** you're willing to pay by simply clicking on and dragging your slider as in the example below:



- Your answer will determine whether or not you buy the information in the following way:
    - The computer will randomly pick a **PRICE**, **p** (p is equally like to be any number between $0 and $5).
    - If p is **LESS than or equal to** the maximum amount you indicated you would be willing to pay, you will buy this information.
        - In this case, p will be subtracted from your budget of $5 AND you will learn which group the ball is in before making a guess.
    - If p is **GREATER** than the maximum amount you indicated you would be willing to pay, you will <u>not</u> buy this information.
        - In this case, you will keep your whole budget of $5 AND you will <u>not</u> learn which group the ball is in before making a guess.

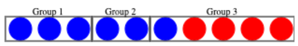
- While this might sound complicated, it is actually **VERY SIMPLE**. **It is in your best interest to simply set the slider to the actual maximum amount you would be willing to pay** to know which group the selected ball is in before making your guess.

Continue Instructions

Buy Information Tasks

How much would you be **willing to pay** to know which of the following Groups the ball is in **before guessing**, in each of the information sources below? Click and drag the sliders to let us know (you must set each slider before continuing).

We have ordered the tasks from the set you most prefer (at the top) to the set you least prefer (at the bottom).



$?

$0 $5

$?

$0 $5

$?

$0 $5

$?

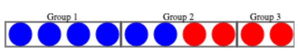
$0 $5

$?

$0 $5

$?

$0 $5



$?

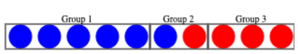
$0 $5

$?

$0 $5

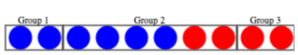
$?

$0 $5



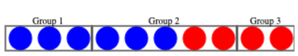
$?

$0 $5



$?

$0 $5

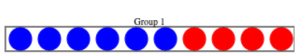


$?

$0 $5

$?

$0 $5



$?

$0 $5

$?

$0 $5

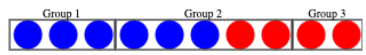
$?

$0 $5

Guessing Question 1

There are 6 blue balls, and 4 red balls. One of these balls will be randomly selected and you earn $10 if you correctly guess the color (blue or red):

You will learn which of the following Groups the ball is in before you guess:



Please tell us what color you will guess if you learn the ball is in each of these possible Groups:

If I learn the ball is in **Group 1**, I will guess the color to be:	◯ **Blue** ◯ **Red**
If I learn the ball is in **Group 2**, I will guess the color to be:	◯ **Blue** ◯ **Red**
If I learn the ball is in **Group 3**, I will guess the color to be:	◯ **Blue** ◯ **Red**

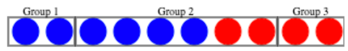
(Remember,these choices determine your actual guess and therefore your payment!)

Final

The computer randomly chose a Ranking Information Question for payment.

Based on your rankings of information sources, we have assigned you the following question.

One of these balls has been randomly selected and you earn $10 if you correctly guess the color (blue or red):



The ball is in **Group 2**.

Please guess the color of the ball:

I guess the color to be:	○ **Blue** ○ **Red**

- **How do you earn the $10 BONUS earning?**

○ By correctly guessing the color of the randomly selected ball.
○ By randomly clicking on things.

- **How do you maximize your chances of winning the $10 BONUS?**

○ Always guess the color of the ball to be Blue.
○ Always make the same guess about the color of the ball for each Group.
○ Make your best guess about the color of the ball for EACH Group separately.

- **Which statement is correct?**

○ I am more likely to receive information from the information source I rank higher (above) than the one I rank lower (below).
○ I am more likely to receive information from the information source I rank lower than (below) the one I rank higher (above).
○ I am equally likely to receive information from any of the information sources.

- **How will it be determined whether or not you buy information in the future guessing round?**

○ Totally randomly
○ If the random price is less than or equal to the maximum amount you indicated you would be willing to pay, you will buy the information; otherwise you won't.
○ If the random price is more than the maximum amount you indicated you would be willing to pay, you will buy the information, otherwise you won't.

Ranking Information Sources

Please drag these information sources on the screen to rank them in order from most favorite (top of the screen) to least favorite (bottom of the screen). The computer will randomly pick two information sources, and you will receive information from the one that you ranked higher before you are asked to make a guess about the color of the randomly selected ball. As in other parts, you will earn a $10 BONUS payment if your guess is correct and $0 if your guess is incorrect.

(To help with your decision, for each Information Source, we include below each Group the guess you made for that Group earlier in a corresponding Guessing Question.)

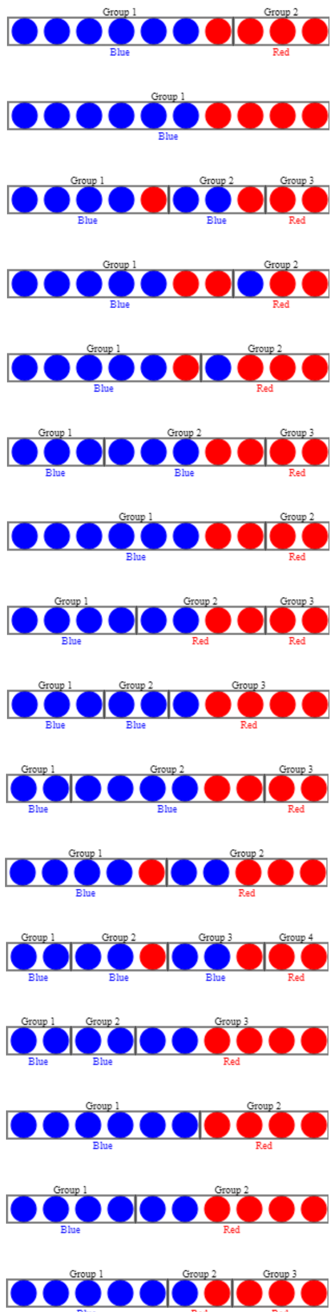


Figure 18: Ranking with Elicited Guesses