Does the Size of the Signal Space Matter?*

Hyundam Je† Daeyoung Jeong‡

August 2025

Abstract

This paper examines whether the value of an informative signal varies with the size of the signal space, representing the number of possible signals. In our experiment, subjects either make a signal purchasing decision (SPD) while predicting the binary outcomes of compound lotteries or make a lottery purchasing decision (LPD) while the lottery includes a free signal regarding the outcome. We tested four distinct lotteries, each associated with varying signal space sizes, yet maintaining identical informational value across signals. Our findings revealed a fascinating dichotomy: in the SPD, subjects are willing to pay more for a signal from a larger signal space, whereas in the LPD, their willingness to pay for a lottery is not associated with the size of the signal. To explain experimental findings, we introduce a novel theoretical framework that integrates reference point theory with uncertainty about a variable of interest, represented by Shannon's entropy.

*We are very thankful to Gary Charness, Syngjoo Choi, Brighton Chotiputsilp, Catherine Eckel, Paul Feldman, Huiyi Guo, Paul J. Healy, Alex Imas, Peter Klibanoff, Silvana Krasteva, Joanna Lahey, Joosung Lee, Jinliang Liu, Daniel Martin, Hyoeun Park, Kyoungwon Seo, Danila Serra, Euncheol Shin, Gerelt Tserenjigmid, Agnieszka Tymula, Leeat Yariv, Sora Youn, and Andreas Ziegler for their helpful advice and comments. Hyundam is especially indebted to Alex Brown for his invaluable support and guidance. We also thank the participants at 2022 World ESA Meeting, KAEA Job Market Conference, Texas Economic Theory Camp, 2022 North-American ESA Meeting, ESA Job Market Seminar, National Taipei University, 2023 Asia-Pacific ESA Meeting, 16th ANZWEE, The Korean Econometric Society Seminar, Caltech Behavioral/Experimental Workshop, 2024 North-American ESA Meeting, Binghamton University, University of Melbourne, Heidelberg University, Kyung Hee University, and University of Seoul for numerous helpful comments. This study was approved by the IRB at Texas A&M University (IRB2022-0462D). All errors are our own.

†School of Economics, University of Seoul, 163 Seoulsirip-daero, Dongdaemun-gu, Seoul, Korea; hje@uos.ac.kr.

‡School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul, Korea; daeyoung.jeong@gmail.com

1 Introduction

Information transmission is fundamental in economic decision-making, yet how the size of signal spaces—the number of possible signals—affects individuals' demand for information has received relatively little attention. Classical economic models, such as those developed by Spence (1973) and Kamenica and Gentzkow (2011), show that signal spaces matching the action spaces are sufficient for effective signaling within the framework of expected utility theory. Although this insight simplifies theoretical analyses by demonstrating that larger signal spaces are unnecessary for informational efficiency, it does not address whether individuals might intrinsically value having more or fewer signals available, independent of their instrumental informational content. Given the prevalence and importance of these models, it is therefore crucial to empirically investigate whether signal space size itself influences information valuation, a possibility that standard expected utility frameworks do not consider.

A sufficiently large signal space can, in principle, allow for more precise signaling and thus facilitate better-informed decisions, mitigating inefficiencies inherent in coarse signaling environments (Crawford and Sobel, 1982; Heumann, 2020). However, from a behavioral perspective, increasing the size of the signal space might introduce complexity, potentially discouraging information acquisition. Cognitive constraints and complexity aversion, well-documented in the literature, suggest that individuals might favor simpler signal spaces due to the psychological costs and interpretative burdens associated with more complex structures (Huck and Weizsäcker, 1999; Sonsino et al., 2002; Halevy, 2007; Moffatt et al., 2015).[1] Thus, empirical evaluation is needed to determine whether, and how, individuals respond to changes in signal space size beyond purely instrumental considerations.

We conducted a controlled laboratory experiment specifically designed to isolate whether the size of a signal space affects how individuals value information, even when the informational content remains constant. Specifically, in our primary experimental

[1]See Section 5.1 for further analysis of how complexity relates to signal space preferences.

condition—the Signal Purchasing Decision (SPD)—subjects were asked to state their willingness to pay for signals that inform predictions about outcomes from compound lotteries. A distinctive feature of our experimental design is that we systematically varied the size of the signal spaces (from two to five signals) while holding constant the informational content across all signals in terms of expected utility theory. According to expected utility theory, subjects should thus exhibit indifference regarding signal space size if informational content remains unchanged. Contrary to this theoretical expectation, our findings indicate that subjects' willingness to pay for signals consistently increases with larger signal spaces, even though the signals provide no additional instrumental value.

To explore this unexpected result, we conducted two follow-up studies to evaluate possible explanations. One possible explanation might be that subjects may not have fully understood the informational value of compound lotteries, potentially misinterpreting or failing to reduce them according to expected utility principles. To address this, we ran a robustness study involving lotteries with explicitly varying values of information. Results from this robustness check indicated that subjects rationally recognized and responded to differences in informational content, suggesting that their valuation in the SPD was not driven by misunderstandings or cognitive errors related to compound lottery structures.

Another explanation is that subjects perceived the value of a lottery as higher when the associated signal was from a larger signal space, even though the signal itself conveyed no additional information. To test this possibility, we conducted the Lottery Purchasing Decision (LPD), a supplementary condition in which signals were provided for free, and subjects were asked to state their willingness to pay to participate in the lotteries. Contrary to the results observed in the SPD, in this LPD scenario, the size of the signal space was not significantly associated with subjects' willingness to pay for lotteries. This contrast suggests that the willingness to pay observed in the SPD does not reflect a general preference for larger signal spaces per se, but rather a context-dependent response.

To reconcile these seemingly contradictory findings between the SPD and the follow-up studies, we propose a novel theoretical framework grounded in Shannon's entropy (Shannon, 1948), which quantifies the reduction in uncertainty. Our central insight is that individuals derive non-instrumental (or intrinsic) utility from the mere resolution of uncertainty itself, independent of any instrumental benefits. This non-instrumental motivation, which we interpret as a form of curiosity, is naturally represented by entropy reduction—a measure of how much a signal reduces the unpredictability of random variables of interest. Specifically, we show that subjects' willingness to pay for signals is systematically related to the amount of uncertainty those signals resolve. This perspective extends traditional economic models, which, under the expected utility framework, characterize the value of information solely in terms of its contribution to improving decision outcomes. Additionally, to account for the contextual differences observed across experimental conditions, we incorporate concepts from reference-dependent valuation. Taken together, these theoretical innovations provide a more comprehensive understanding of how individuals value information, highlighting the critical role of non-instrumental motivations—particularly curiosity—in information acquisition.

This paper makes three key contributions to the literature on information valuation. First, it introduces a novel experimental design that isolates whether the size of a signal space affects how individuals value information. By varying signal space size while holding informational content constant in terms of expected utility theory, the design allows for a clean identification of the role of non-instrumental considerations. Second, using this design, we provide new empirical evidence that disentangles non-instrumental from instrumental motives for acquiring information, demonstrating that individuals value uncertainty reduction even when it yields no instrumental benefit. Third, we propose a theoretical framework that incorporates non-instrumental motivations, quantified via entropy reduction, alongside standard instrumental reasoning. This framework accounts for observed patterns in willingness to pay across different informational contexts.

The remainder of the paper proceeds as follows. In Section 2, we detail our main treatment, SPD, outlining theoretical predictions based on expected utility and presenting empirical findings. Section 3 presents robustness checks and supplementary experimental evidence to further clarify observed behaviors. Section 4 presents our theoretical framework, incorporating non-instrumental motivations. Section 5 situates our findings within broader theoretical contexts, and Section 6 discuss related literature. We conclude with Section 7.

2 Main Treatment: Signal Purchasing Decision

2.1 Experimental Design

In our main treatment, the Signal Purchasing Decision (SPD) includes four lotteries, illustrated in Figure 1. In the experiment, subjects play all four lotteries. For each lottery, multiple boxes are available, each containing ten balls that are either red or blue. The computer randomly selects one box, with each box having an equal probability of being chosen. Then, one ball is drawn at random from the selected box. Before the draw, subjects are asked to predict the color of the ball. A correct prediction earns 100 points, with each point equivalent to 0.01 USD.

Each box is labeled as Box Xn, where $X \in \{\mathrm{R}, \mathrm{B}, \mathrm{G}\}$ and $n \in \{5, 6, 7, 8, 9\}$.[2] Here, X signifies the predominant color of the balls contained within the box, and n indicates the total count of balls of that color. For instance, Box R7 contains a majority of red balls, specifically seven red balls.[3] Note that Box G5 is the sole

[2] Ambuehl and Li (2018) elicited the demand for informative signals and found that people significantly prefer information that may lead to certainty. Therefore, to avoid the certainty effect, we exclude the box of $n = 10$.

[3] In the actual experiment, the boxes were referred to as Box R, Box B, Box G, Box RR (if there were multiple Box R in the same lottery), and Box BB (if there were multiple Box B in the same lottery). Numerical labels were deliberately avoided to encourage subjects to rely more on intuition.

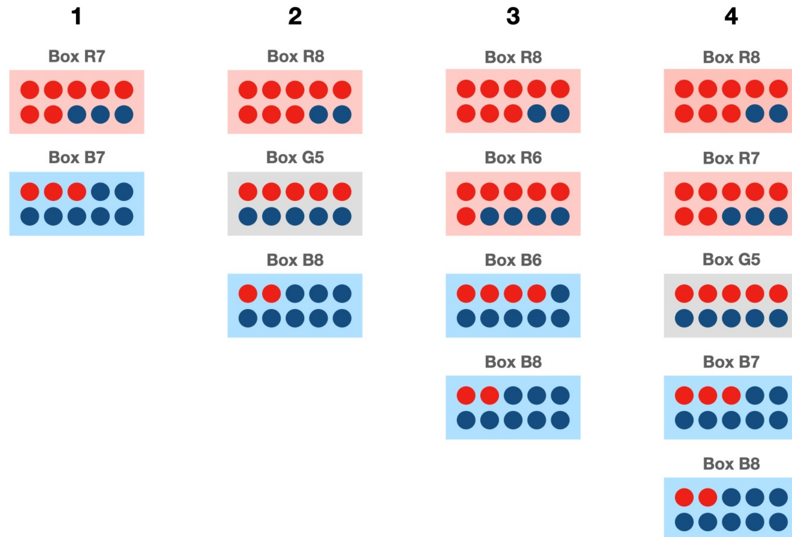

Figure 1: Four lotteries

instance of Box Gn, as Box G invariably holds five red balls and five blue balls, maintaining an equal distribution between the two colors.

Before making their prediction, subjects had the option to purchase a costly signal using their 100-point endowment. In each lottery, we elicited their willingness to pay (WTP) for the signal using the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964), described below. Depending on the outcome of the BDM mechanism, subjects either received the signal or not. If a subject received a signal, the computer revealed the box that had been randomly selected for that lottery, and the subject then made their color prediction with this information. For example, in Lottery 2 (Box R8, G5, and B8), a subject who received the signal and learned that Box R8 was selected would know that betting on red gives an 80% chance of winning, rather than 50% without the signal. If the subject did not receive a signal, they made their prediction without knowing which box had been selected. In this case, the probability of winning remained 50%, regardless of their guess. The full sequence of events for each lottery is illustrated in Figure 2.

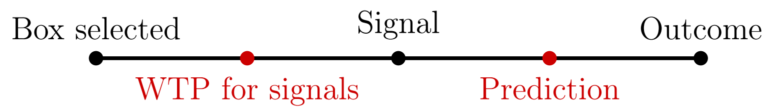

Figure 2: Timeline of Signal Purchasing Decision

To elicit WTP, we used the BDM mechanism (Becker et al., 1964) in a multiple price list format. The structure of the BDM questions is shown in Table 1. Instead of submitting 100 separate decisions, subjects indicated the highest price at which they were willing to purchase the signal, thereby identifying a "switching point" between Option A (purchasing the signal at a given price) and Option B (not purchasing it).[4] After subjects submitted their WTP (i.e., switching point) for the signal, a random number between 1 and 100 was drawn for each lottery to determine the signal price. If the stated WTP exceeded the drawn price, the subject received the signal; otherwise, they did not. They then proceeded to make their prediction for that lottery.

Q#	**Option A**	Choices	**Option B**
1	Buying a Signal for 1 point		Not Buying a Signal
2	Buying a Signal for 2 points		Not Buying a Signal
3	Buying a Signal for 3 points		Not Buying a Signal
4	Buying a Signal for 4 points		Not Buying a Signal
⋮	⋮	⋮	⋮
97	Buying a Signal for 97 points		Not Buying a Signal
98	Buying a Signal for 98 points		Not Buying a Signal
99	Buying a Signal for 99 points		Not Buying a Signal
100	Buying a Signal for 100 points		Not Buying a Signal

Table 1: The BDM mechanism in the SPD

[4] A common issue with the BDM mechanism is its complexity, which can lead to biased responses in some settings. See Noussair et al. (2004) for a discussion. To minimize confusion, subjects reported their maximum willingness to pay directly rather than responding to 100 separate price options. Before making their actual decisions, subjects were also shown a worked example illustrating how the BDM mechanism operates. Importantly, any potential bias in stated values—whether upward or downward—does not undermine the purpose of using BDM in our study, which is to compare relative valuations across signals and lotteries rather than to elicit precise point estimates.

2.2 Procedural Details

This paper includes three between-subjects studies: the main treatment, SPD, which is discussed in the preceding subsection, and two follow-up studies presented in Section 3.1. In each study, subjects made lottery-related decisions specific to that study, and then responded to an ambiguity attitude question described in Appendix D. One of the decisions made in each study was randomly selected for payment, and subjects earned points based on the outcome of their decision. Each point was equivalent to 0.01 USD.

A total of 467 subjects participated in the experiments through Prolific, which is an online platform for recruiting research participants.[5] Specifically, 179 subjects took part in the SPD, and 130 and 158 subjects participated in the follow-up studies: the SPD with Varying VOI and the LPD, respectively. On average, subjects spent 10 minutes and earned $3.32, including a $2.20 base payment.

2.3 Theoretical Considerations and Hypotheses

A critical aspect of this experiment is the diversity in the quantity of boxes present in each lottery, which directly translates to the varying number of available signals: Lottery 1 has two boxes, Lottery 2 has three, Lottery 3 has four, and Lottery 4 has five. Notably, despite these differences, the ex-ante value of information remains constant across all lotteries. The value of information, In this context, the value of information is defined as the difference between the expected utility with the signal and the expected utility without it. This can be explained by expected utility theory, which posits that the value derived from obtaining information (or signals, in this case) is essentially the utility gain from making a more informed decision versus a less informed one. The theory suggests that while the availability of signals varies, the

[5] Gupta et al. (2021) demonstrated that Prolific can be a reliable source of high-quality data. For details on Prolific's subject pool, see Palan and Schitter (2018). In all three of our studies, only US subjects participated.

non-instrumental value of being better informed does not fluctuate across different scenarios, as long as the informational content of the signals remains constant.

According to expected utility theory, the decision-makers assign a probability $p(\omega)$ to the state $\omega \in \Omega$ to evaluate a lottery.

$$U_{EU}(L_i) \equiv E(u(L_i)) = \sum_{\omega \in \Omega} p(\omega) u(L_i|\omega) = 0.5 \times u(100).$$

In this context, ω represents the color of the drawn ball. Importantly, from an ex-ante perspective, the expected utility of lottery i with a signal $s_i \in S_i$, which indicates the selected box, aligns with the expected utility without the signal. The expected utility, considering the signal, can be expressed as:

$$U_{EU}(L_i|S_i) \equiv E_{s_i}[E(u(L_i|\omega, s_i)|s_i)] = \sum_{\omega \in \Omega} \sum_{s_i \in S_i} p(\omega|s_i) u(L_i|\omega, s_i) = 0.7 \times u(100) \ \ \forall i$$

This formulation demonstrates that, irrespective of from which a signal is provided, the expected utility for any given lottery remains constant. This equality underscores the theoretical premise that the size of the signal space does not alter the expected utility of participating in the lottery, assuming the signal's information content is fully integrated into the decision-making process.

Therefore, according to the expected utility theory, in our experiment, the value of information $VOI(S_i|L_i)$ is defined as

$$VOI(S_i|L_i) \equiv U_{EU}(L_i|S_i) - U_{EU}(L_i) = 0.2 \times u(100) \tag{1}$$

and constant at 20 for any lottery L_i for the risk-neutral expected utility maximizer.

From this theory, we propose that if the value of information entirely dictates the worth of a signal, i.e., $WTP(S_i|L_i) = VOI(S_i|L_i)$, where $WTP(S_i|L_i)$ represents the willingness to pay for a signal $s \in S_i$ for lottery L_i, then the willingness to pay for signals across all four lotteries should be uniform. Therefore, we formulate the following hypothesis:

Hypothesis 1. *The value of information fully determines the worth of a signal. Therefore, the size of the signal space does not influence the willingness to pay for the signal:* $WTP(S_1|L_1) = WTP(S_2|L_2) = WTP(S_3|L_3) = WTP(S_4|L_4)$.

2.4 Results: Willingness to Pay Increases with Signal Space Size

Lottery	$\lvert S_i \rvert$	$WTP(S_i \mid L_i)$	Number
1	2	23.6	179
2	3	24.9	179
3	4	25.8	179
4	5	29.8	179

Table 2: Elicited values for $WTP(S_i|L_i)$.

Table 2 presents elicited values for the willingness to pay for a signal $s \in S_i$ for lottery L_i ($WTP(S_i|L_i)$), expressed in points, where $|S|$ denotes the size of the signal space. Surprisingly, subjects show a higher willingness to pay for signals when they are associated with larger signal spaces.[6] The Cuzick non-parametric trend test results show that the size of the signal space is significant ($p = 0.005$).

Table 3 presents the regression results, showing a strong positive relationship between signal space size and willingness to pay for signals (F-test, $p < 0.001$). This suggests that willingness to pay increases with the size of the signal space. Consequently, we reject Hypothesis 1 and state Result 1.

Result 1. *The willingness to pay for a signal increases with the size of signal space.*

[6] Appendix A shows that subjects predominantly followed the signal when it was informative, suggesting they comprehended the information structure. Appendix B further shows that subjects choosing lotteries with larger signal spaces earned lower payoffs, consistent with the interpretation that they overvalued such signals.

	$WTP(S_i|L_i)$
	(1)
Signal Space Size	1.934***
	(0.395)
Constant	21.218***
	(1.650)
Observations	716
R-Squared	0.010

Notes: Robust standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: The effect of the size of signal space on the willingness to pay for a signal

The observed relationship $\frac{\partial WTP(S_i|L_i)}{\partial |S_i|} > 0$ motivates the key question of our paper: why does the size of the signal space matter in our experiment? The remainder of the paper addresses this question.

3 Robustness and Additional Experimental Evidence

To better understand the surprising pattern observed in the SPD, we conducted two follow-up studies aimed at evaluating the plausibility of potential explanations.

3.1 Robustness Study: the SPD with Varying VOI

One possible explanation is that subjects may not fully understand the value of information for the compounded lotteries, $VOI(S_i|L_i)$. In the SPD, the value of information was held constant across all lotteries, so it is unclear whether subjects respond to variation in $VOI(S_i|L_i)$. To investigate this, we conducted a robustness study using lotteries with varying values of information. This design is referred to as SPD with varying VOI.

The procedure of this study was identical to that of the SPD: subjects were asked to submit their willingness to pay for signals in a series of lotteries. However, to

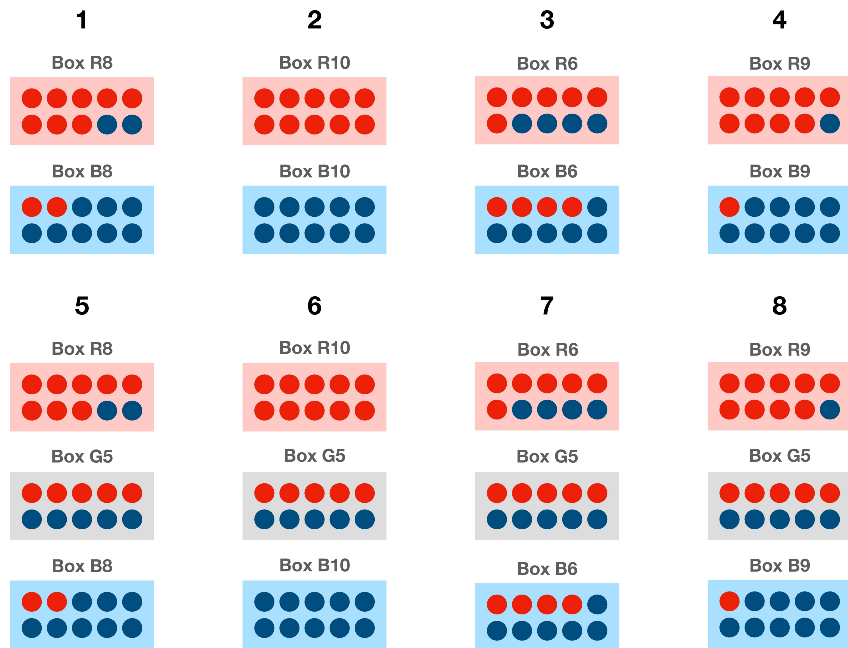

Figure 3: Lotteries in the SPD with Varying VOI

examine whether subjects understood the instrumental value of information, we used eight different lotteries with varying values of information, as illustrated in Figure 3. If subjects correctly understood the framework, they would be more willing to pay for signals with higher instrumental value.

Table 4 summarizes the details of the lotteries and reports the submitted values for the willingness to pay for the signal in each lottery, $WTP(S_i|L_i)$. Lotteries 1 to 4 each include two boxes—Box Rn and Box Bn—where $n \in 5, 6, 7, 8, 9, 10$, resulting in a signal space of size 2. Lotteries 5 to 8 contain three boxes—Box Rn, Box Gn, and Box Bn—corresponding to a signal space of size 3.

The fourth column reports the value of information for each lottery, $VOI(S_i|L_i)$, which serves as the theoretical benchmark for a risk-neutral utility maximizer. The fifth column shows the submitted $WTP(S_i|L_i)$ values. Consistent with theoretical predictions, subjects were more willing to pay for signals with higher instrumental value. A chi-square test rejects the null hypothesis that the willingness to pay was

Questions	Signal Space Size	Winning Prob With Signals	$VOI(S_i\|L_i)$	$WTP(S_i\|L_i)$
1	2	0.80	30	24.1
2	2	1.00	50	38.0
3	2	0.60	10	24.8
4	2	0.90	40	37.8
5	3	0.70	20	28.4
6	3	0.83	33.3	34.7
7	3	0.57	6.7	23.7
8	3	0.77	26.7	30.8

Table 4: $VOI(S_i|L_i)$ and $WTP(S_i|L_i)$

submitted randomly ($p < 0.001$).

	$WTP(S_i\|L_i)$	
	(1)	(2)
$VOI(S_i)$	0.251***	0.273***
	(0.065)	(0.067)
Signal Space Size		1.505
		(1.062)
Constant	22.322***	17.969***
	(1.982)	(3.719)
Observations	1040	1040
R-Squared	0.020	0.020

Notes: Robust standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: The effect of the value of information on WTP

The regression results presented in Table 5 further indicate that subjects have an understanding of the value of information in the signal purchasing environment. The first row of the table suggests that the submitted values of $WTP(S_i|L_i)$ are positively correlated with the theoretical predictions $VOI(S_i|L_i)$, which represent the value of information for a risk-neutral individual in the expected utility model.[7]

[7] The second row of the table shows that the size of the signal space has no significant effect

Therefore, we can reasonably conclude that the behavior observed in the SPD is not driven by a misunderstanding of the signaling structure associated with compound lotteries. Subjects appeared rational enough to understand the value of information clearly and adjusted their willingness to pay accordingly.

Result 2. *Willingness to pay for a signal is positively associated with its instrumental value.*

3.2 Lottery Purchasing Decision

In the SPD with varying VOI, we observe that WTP for a signal is positively related to the signal's value of information. However, the preference for larger signal spaces in the SPD remains unexplained: why does WTP increase with the size of the signal space, even when VOI is theoretically held constant and independent of signal space size?

One possible explanation is that subjects mistakenly believe that signals from larger signal spaces have greater instrumental value. This would imply $\frac{\partial U_{EU}(L_i|S_i)}{\partial |S_i|} > 0$, where $U_{EU}(L_i \mid S_i)$ denotes the ex-ante expected utility of the lottery conditional on receiving a signal. This is a natural hypothesis to investigate, as the size of the signal space does not directly affect $VOI(S_i \mid L_i)$, but it may influence $U_{EU}(L_i \mid S_i)$, which is the only component of $VOI(S_i \mid L_i)$ that depends on signal space size, as shown in Equation (1).

To examine this, we conducted an additional study: the Lottery Purchasing Decision (LPD). In the LPD, the focus shifted from assessing the value of signals in the four lotteries to evaluating the value of the lotteries themselves, with signals provided at no cost. The lotteries used in this study were identical to those in the SPD. Specifically, subjects indicated their willingness to pay to participate in each lottery. Before

on the submitted value in this robustness study, although the estimates remain positive and are consistent with the results from the SPD. This may be because the variation in signal space size in this robustness study is limited (from 2 to 3), whereas in the SPD it ranges from 2 to 5.

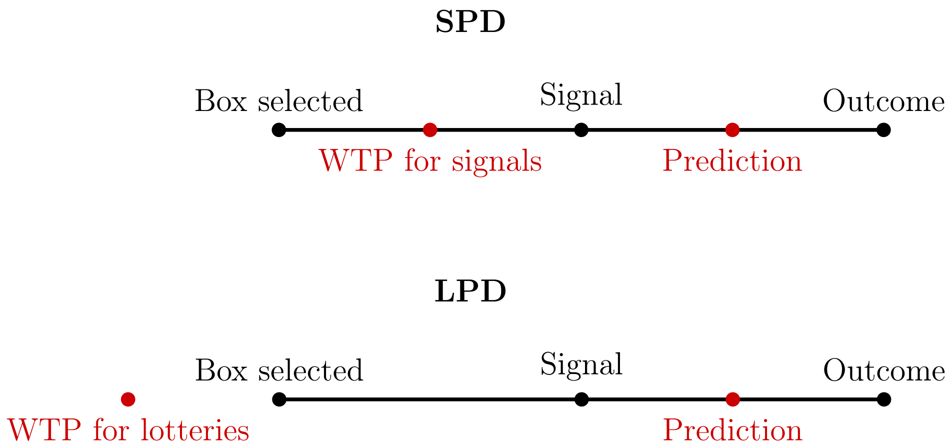

Figure 4: Comparison of Timelines: SPD vs. LPD

making their color prediction, they were informed which box had been selected. The timeline for this study is shown in Figure 4.

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The BDM procedure in the LPD mirrored that of the SPD, as shown in Table 6. Before engaging with the lotteries, subjects indicated the maximum number of points they were willing to pay to play each lottery. After submitting their valuations for all four lotteries, one was randomly selected. A random number between 1 and 100 was then drawn to serve as the substitute reward. If the bid exceeded this amount, the subject participated in the lottery; otherwise, the substitute reward was given instead. Upon participating, the subject was informed of the selected box and asked

Q#	**Option A**	Choices	**Option B**
1	Playing the lottery		Receiving 1 point
2	Playing the lottery		Receiving 2 points
3	Playing the lottery		Receiving 3 points
4	Playing the lottery		Receiving 4 points
⋮	⋮	⋮	⋮
97	Playing the lottery		Receiving 97 points
98	Playing the lottery		Receiving 98 points
99	Playing the lottery		Receiving 99 points
100	Playing the lottery		Receiving 100 points

Table 6: The BDM mechanism in the LPD

to predict the color of the drawn ball.

Lottery	$\|S_i\|$	$WTP(L_i\|S_i)$	Number
1	2	52.9	158
2	3	48.9	158
3	4	51.0	158
4	5	52.7	158

Table 7: Elicited values for $V(L_i|S_i)$.

Table 7 presents the willingness to pay for each lottery given a signal ($WTP(L_i|S_i)$), expressed in points. In the LPD, there is no clear association between the size of the signal space and the valuation of equivalent lotteries, as confirmed by the Cuzick non-parametric trend test ($p = 0.574$). This finding is further supported by the regression analysis in Table 8, where the size of the signal space has no effect on the value of lotteries, denoted as $V(S_i|L_i)$.[8]

Result 3. *The size of the signal space is not associated with the willingness to pay for a lottery, given a signal.*

[8]F-test p-values are 0.7502, 0.7504, and 0.7502 for each column.

	$WTP(L_i \mid S_i)$
	(1)
Signal Space Size	0.160
	(0.502)
Constant	50.978***
	(1.798)
Observations	632
R-Squared	0.000

Notes: Robust standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: The effect of $|S_i|$ on WTP

4 Complementary Mechanism: Non-Instrumental Values of Information

Our experimental findings suggest that subjects' behavior cannot be fully explained by classical expected utility theory or by the instrumental value of information alone. In particular, willingness to pay for a signal in the SPD increases with the size of the signal space—a pattern not observed in the LPD. These discrepancies suggest that additional factors may influence subjects' decision-making.

In this section, we propose an alternative theoretical framework that incorporates a non-instrumental component into the valuation of information. Our conjectures are premised on the idea that, beyond the instrumental benefits—such as improved decision-making and reduced uncertainty—individuals derive extra value from acquiring information per se. In other words, subjects may be motivated not only by the practical utility of information but also by an inherent, non-instrumental desire for knowledge, which could manifest as curiosity.

We stress that this perspective does not imply that subjects disregard to the instrumental value of information. As demonstrated in Section 3.1, subjects accurately assess the instrumental benefits predicted by expected utility theory. Rather, our argument extends this view by suggesting that individuals also place value on the mere resolution of uncertainty, regardless of its direct impact on decision outcomes.

Recent findings in neuroscience and psychology support this broader interpretation. For example, Bennett et al. (2016) and Gottlieb and Oudeyer (2018) show that individuals are motivated by factors beyond the immediate practical benefits of information. Similarly, Kobayashi and Hsu (2019) and Lau et al. (2020) provide evidence that non-instrumental motives—such as pure curiosity—play a significant role in information-seeking behavior.

By integrating these insights, we contend that subjects in our studies are influenced by a non-instrumental desire for information. This perspective extends the traditional expected utility framework and offers a more comprehensive understanding of human information acquisition.

4.1 Empirical Evidence from the SPD

We conjecture that the non-instrumental value of information observed in our experiment is driven by curiosity—a fundamental desire to reduce uncertainty, independent of any direct impact on decision outcomes. This intrinsic motive leads individuals to seek information even when it offers no instrumental benefit, consistent with recent findings in neuroscience and psychology.

This form of curiosity depends on how uncertainty is framed within the decision environment. In particular, when deciding whether to purchase a signal that reveals the box in which the ball is located in the SPD, subjects appear to focus on the uncertainty associated with the box.

To quantify this uncertainty, we employ Shannon's entropy (Shannon, 1948), which provides a measure of the unpredictability or information content of a random variable. Shannon's entropy is defined as

$$H(X) = -\sum_{x} p(x) \log p(x),$$

where X denotes a random variable. We then use this measure to capture the *non-instrumental value* of information by examining the reduction in uncertainty of X due to the knowledge of another variable Y. This reduction is quantified by the mutual information, which is given by

$$\begin{aligned} I(X;Y) &= H(X) - H(X \mid Y) \\ &= \left(-\sum_{x} p(x) \log p(x)\right) - \left(-\sum_{y} p(y) H(X \mid Y = y)\right) \\ &= \sum_{y} p(y) \left[H(X) - H(X \mid Y = y)\right] \\ &= \sum_{x} \sum_{y} p(x, y) \log \frac{p(x, y)}{p(x) p(y)}. \end{aligned}$$

In this framework, the value of information is interpreted as the reduction in uncertainty when transitioning from a scenario without the signal to one with the signal.

In the SPD, we let X correspond to the chosen box, denoted by B_i for lottery i. For example, consider lottery 1, which has two boxes; its entropy is given by

$$H(B_1) = -2\left(\frac{1}{2} \log \frac{1}{2}\right).$$

Similarly, lottery 2 has three boxes and its entropy is

$$H(B_2) = -3\left(\frac{1}{3} \log \frac{1}{3}\right),$$

so that

$$H(B_1) < H(B_2) < H(B_3) < H(B_4).$$

Since the signal S_i fully reveals the selected box, the conditional entropy is

$$H(B_i \mid S_i) = -(1 \log 1) = 0.$$

Therefore, for lottery i in the SPD, the mutual information is

$$I(B_i; S_i) = H(B_i) - H(B_i \mid S_i) = H(B_i).$$

We summarize this argument in the following conjecture.

Conjecture 1 (Entropy-Based Valuation)**.** *A subject's willingness to pay for a signal in the SPD is positively related to the uncertainty of the box B_i, as measured by $H(B_i)$. Specifically, the willingness to pay increases in the mutual information, i.e., $I(B_i; S_i) = H(B_i) - H(B_i \mid S_i)$. We call this non-instrumental value of information.*

	$V(S_i \mid L_i)$ (1)
$NVOI_{SPD}$	3.689***
	(0.766)
Constant	20.074***
	(1.785)
Observations	716
R-Squared	0.009

Notes: Robust standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: The effect of the NVOI on the value of the signal space

Table 9 shows that our framework aligns with the experimental results. Here, $NVOI_{SPD}$ denotes the non-instrumental value of information $I(B_i; S_i)$ for each lottery

i, and the value of the signal in the SPD, $V(S_i|L_i)$, is significantly positively correlated with this measure.

The observation that a subject's willingness to pay in the SPD increases with the non-instrumental value of information $I(B_i; S_i)$ suggests that individuals value signals not solely for their instrumental benefits—such as improved decision accuracy—but also for their ability to reduce epistemic uncertainty. In other words, even when the instrumental value remains constant across lotteries, subjects appear to assign additional non-instrumental value to signals that resolve greater uncertainty.

4.2 Further Insights from the LPD

In an entropy-based approach, the domain over which entropy is evaluated is not fixed but may depend on how the decision problem is framed. In other words, the relevant source of uncertainty—what the individual is curious about—can shift depending on the structure of the task.

In the SPD, when deciding whether to purchase a signal that provides information about the box containing the ball, subjects may ask which box the ball is likely in, focusing primarily on the uncertainty regarding the box. By contrast, in the LPD, when deciding whether to purchase a lottery about the color of the ball, subjects may ask which ball is likely to be chosen, concentrating instead on the uncertainty regarding the ball.

Conjecture 2 (Entropy-Based Valuation)**.** *The subject's willingness to pay for a lottery in the LPD is associated with the uncertainty of ball Q_i, measured by $H(Q_i)$, for any lottery i.*

Specifically, in the LPD, the willingness to pay would be positively associated with the mutual information, which quantifies the reduction in uncertainty a ball Q_i by comparing the reference point, which is the state of uncertainty of without the signal, to the updated state with the signal. This raises the question of what constitutes the natural reference point for subjects in evaluating the non-instrumental value of information. We argue that it depends on the variable of interest.

In the SPD, as conjectured in Conjecture 1, subjects deciding whether to purchase a signal focus on which box is selected. Their attention is directed primarily toward the identity of the box, B_i. Therefore, any signal that provides information about which box the ball is chosen from is considered valuable, as it reduces the uncertainty regarding the box and aligns with the subject's primary goal of identifying the box where the ball is located.

By contrast, in the LPD, not all signals are necessarily regarded as valuable. Here, subjects focus on the color of the ball rather than the box (note that the term "signal" is not even used in the LPD). From this perspective, the gray box and the red or blue boxes may be perceived differently. For example, subjects who pay the entry fee to participate in the lottery might view a winning probability of 50% as a disadvantage relative to their expectations. More specifically, we assume that subjects anticipate at least a 50% chance of winning when they choose to participate, and thus take this as a reference point. Accordingly, their perceptions of the gray box and the other boxes might differ.

To formally incorporate reference point considerations into our framework, we define the reduction in uncertainty about a variable X conditional on information about another variable Y as follows:

$$v(Y|X,r) = \begin{cases} (r(X) - H(X|Y))^{\rho} & \text{if } H(X|Y) \leq r(X) \\ \lambda(-(r(X) - H(X|Y))^{\rho} & \text{if } H(X|Y) > r(X), \end{cases}$$

where $r(X)$ is the reference level of uncertainty on X and $H(X|Y)$ is the uncertainty of X given Y. Here, ρ is the parameter that captures the curvature of the value function, reflecting diminishing sensitivity to changes in uncertainty, while λ captures the asymmetry in responses, assigning greater weight to increases in uncertainty above the reference point. This framework captures how individuals evaluate reductions in uncertainty when they have non-instrumental motivations, emphasizing the disproportionate reaction to uncertainty that exceeds the reference point. It also highlights how individuals may place extra value on reductions in uncertainty below the reference level and respond more strongly when uncertainty rises above that level.

Now we have the following conjecture:

Conjecture 3 (Reference Dependence)**.** *The subject's willingness to pay is associated with the expected value of uncertainty reduction given the reference point r, $\hat{v}(S_i|X, r)$. We refer to this as the Non-instrumental Value of Information with Reference Dependence.*

In the SPD, the variable X is the chosen box, B_i for the lottery i.

$$H(B_1) = -2\left(\frac{1}{2}\log\frac{1}{2}\right) < H(B_2) = -3\left(\frac{1}{3}\log\frac{1}{3}\right) < H(B_3) < H(B_4)$$
$$H(B_i|S_i) = -(1\log 1) = 0$$

As argued above, the reference point for L_i in SPD is the uncertainty without the information, $H(B_i)$. Therefore,

$$\begin{aligned}\hat{v}(S_i|B_i, r) &\equiv \sum_{s_i} p(s_i)\left[r(B_i) - H(B_i|S_i = s_i)\right]^{\rho} \\ &= \sum_{s_i} p(s_i)\left[H(B_i) - H(B_i|S_i = s_i)\right]^{\rho}\end{aligned}$$

Then, we get the following order for the non-instrumental value of information, NVOI:

$$\hat{v}(S_1|B_i, 0) < \hat{v}(S_2|B_i, 0) < \hat{v}(S_3|B_i, 0) < \hat{v}(S_4|B_i, 0)$$

This order reflects the increasing value of information as the uncertainty of the chosen box B_i increases. The calculation shows how the non-instrumental value of information is higher for lotteries with greater initial uncertainty, given that the reduction in uncertainty (from the reference point $H(B_i)$) is more significant. This aligns with the conjecture that subjects' willingness to pay is associated with the expected value of uncertainty reduction.

In the LPD, the random variable X is the chosen ball, Q_i for lottery i.

$$H(Q_i) = -2\left(\frac{1}{2}\log\frac{1}{2}\right) = 1 \text{ for all } i.$$

$$H(Q_1|S_1) = -2\left((.7 \times .5)\log(.7 \times .5) + (.3 \times .5)\log(.3 \times .5)\right)$$

For the subjects in the LPD, any signal that leads to a higher degree of uncertainty than 50:50 odds is considered a "loss." Therefore, the reference point $r(Q_i)$ should be less than $H(Q_i) = 1$.

$$\hat{v}(S_i|Q_i, r) \equiv \sum_{s_i} p(s_i)\left[r(Q_i) - H(Q_i|S_i = s_i)\right]^\rho$$

By taking $r(Q_i) = 0.99$, we get the following order in a large set of parameter values:

$$\hat{v}(S_2|Q_i, .99) < \hat{v}(S_4|Q_i, .99) < \hat{v}(S_3|Q_i, .99) < \hat{v}(S_1|Q_i, .99) \tag{2}$$

This ordering reflects the non-instrumental value of information in the LPD scenario, considering the reference point for uncertainty reduction. By setting the reference point slightly below the maximum entropy, we capture the subjects' preference for signals that significantly reduce uncertainty.

Table 10 examines the extent to which our framework aligns with the experimental results. $NVOI_{SPD}$ and $NVOI_{LPD}$ represent the non-instrumental value of information for the SPD and LPD, respectively, as defined by our framework, which incorporates uncertainty reduction and the reference point. The value of the signal in the SPD ($V(S_i|L_i)$) is significantly positively correlated with $NVOI_{SPD}$, but not

	$V(S_i \mid L_i)$	$V(L_i \mid S_i)$
	(1)	(2)
$NVOI_{SPD}$	1.933***	0.675
	(0.414)	(0.525)
$NVOI_{LPD}$	-0.002	1.287**
	(0.464)	(0.545)
Constant	21.224***	46.473***
	(2.214)	(2.577)
Observations	716	632
R-Squared	0.010	0.004

Notes: Robust standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: The effect of the NVOI on the value of the signal space and the lottery

with $NVOI_{LPD}$. By contrast, the regression results show that the value of the lottery in the LPD ($V(L_i|S_i)$) is significantly correlated with $NVOI_{LPD}$, but not with $NVOI_{SPD}$. These results demonstrate that our framework is consistent with the experimental findings.

Our findings offer important insights into how individuals value information. Firstly, they highlight that individuals also place weight on non-instrumental motivations when evaluating information, even when instrumental information is fixed. Results from the SPD indicate that subjects assign greater non-instrumental value to signals offering substantial uncertainty reduction, reflecting curiosity-driven behavior independent of immediate practical utility. Importantly, we also find evidence from the LPD that non-instrumental value matters: even when signals are freely provided, individuals' willingness to pay for participation in the lottery is systematically related to how much uncertainty the signals resolve.

These results underscore the contextual nature of information valuation, demonstrating that identical information can be perceived differently depending on whether individuals actively seek it or passively receive it. As a result, economic and behavioral models of information acquisition should integrate non-instrumental motivational factors, particularly curiosity and reference-dependent valuations, to more accurately predict real-world decision-making behaviors. Incorporating Shannon's entropy and reference dependence into theoretical frameworks thus provides a comprehensive and robust mechanism for capturing the nuanced ways in which individuals value information beyond mere instrumental utility.

5 Discussion

5.1 Complexity Aversion

At first glance, one might interpret the observed behavior in the Signal Purchasing Decision (SPD) as an instance of complexity aversion (Oprea, 2020; Gabaix, 2025). In this interpretation, subjects might value signals more as the number of boxes (i.e., possible states) increases, not necessarily because of the information conveyed, but because a more complex environment creates cognitive burden or discomfort. Thus, they may be willing to pay more for signals in larger signal spaces to simplify the decision problem. This interpretation seems plausible given prior evidence that people often avoid cognitively demanding tasks and may favor simpler options in decision environments (e.g., Simon, 1955; Caplin and Dean, 2015).

However, we argue that such an explanation is insufficient in our setting and that a more precise account is needed. The concept of uncertainty, as formally defined in information theory by Shannon (1948), provides a better explanation of the observed behavior. Shannon's entropy, defined as $H(X) = -\sum_x p(x) \log p(x)$ for a random variable X, quantifies the average unpredictability—or uncertainty—of outcomes. In our experiments, the signals reduce entropy by providing information about a hidden variable (e.g., which box was chosen), and this reduction in entropy corresponds to what we define as the value of information. Importantly, Shannon entropy is not about complexity in the cognitive sense, but about the statistical uncertainty inherent in a distribution.

In contrast, complexity in behavioral economics typically refers to the difficulty of representing, processing, or acting upon a decision structure—often arising from features such as nested conditionals, extensive branching, unfamiliar choice architectures, or memory demands. In the literature, complexity is thus defined either as the structural and cognitive cost of executing or understanding a rule, or as a disutility term directly incorporated into decision-making models (e.g., Oprea, 2020; Guan and Oprea, 2024; Gabaix, 2025). However, while the number of boxes in our setting increases the entropy of the underlying state space, it does not increase the procedural or representational complexity faced by subjects. The task remains simple and transparent across conditions, and subjects do not face additional reasoning steps or memory demands as the number of boxes increases. Therefore, what may appear as complexity aversion is more accurately understood as a preference for uncertainty reduction.

Taken together, the observed increase in subjects' willingness to pay for signals from larger signal spaces in the SPD is more convincingly explained by a preference for reducing uncertainty rather than by an aversion to complexity.

5.2 Cumulative Prospect Theory

Given that our proposed mechanism incorporates reference dependence, it is natural to consider whether Cumulative Prospect Theory (CPT), proposed by Kahneman and Tversky (1992) as an extension of the original framework introduced in Kahneman and Tversky (1979), could also explain the behavioral patterns observed in our experiments. As an extension of the original prospect theory, CPT accommodates nonlinear probability weighting and differential sensitivity to gains and losses, providing a more flexible framework than expected utility theory for modeling choice under risk.

While CPT captures many behaviors under risk, it focuses on instrumental outcomes and does not account for the intrinsic or non-instrumental motives highlighted in our study. Using standard parameter values from the literature, CPT yields identical predictions for both the SPD and the LPD, as it evaluates signal value solely based on its effect on expected outcomes. Detailed analysis and resulting preference orderings are provided in Appendix C.

This consistency in predictions contrasts with our empirical findings: subjects display a distinct preference for larger signal spaces in the SPD but not in the LPD, even when the instrumental value of information is held constant. CPT cannot account for this divergence without assuming that decision-makers fundamentally shift their underlying preferences or utility parameters between tasks—an assumption that is neither parsimonious nor theoretically grounded.

In contrast, our framework accounts for the behavioral differences by allowing both the reference point and the focus of evaluation to shift with the decision context. Specifically, in the SPD, the subject's attention is directed toward resolving uncertainty about the identity of the box, whereas in the LPD, it shifts to the color of the ball, which is more directly tied to the final payoff. Because of this contextual shift, individuals assess information in relation to different types of uncertainty. This allows a single mechanism—grounded in Shannon's entropy and reference-dependent valuation—to account for both patterns without modifying core parameters. In this view, the observed preference for signals from larger spaces in the SPD is better understood as a manifestation of curiosity about a particular dimension of uncertainty.

5.3 Ambiguity Attitudes

One might interpret the variation in willingness to pay for signals, despite equal instrumental value, as a failure to reduce compound lotteries to their simple equivalents (for example, Lottery 3 can be reduced to Lottery 1). According to Halevy (2007), ambiguity neutrality is strongly associated with the ability to perform such reductions accurately. That is, ambiguity-neutral individuals are expected to behave in line with expected utility theory, whereas ambiguity-averse or ambiguity-seeking individuals are less likely to correctly reduce compound lotteries to their simple equivalents.

To assess this possibility, we measured subjects' ambiguity attitudes using a canonical Ellsberg task (Ellsberg, 1961). We then categorized them into ambiguity-averse, -neutral, or -seeking types and examined whether these attitudes systematically affected their willingness to pay for signals ($V(S_i|L_i)$) or lotteries ($V(L_i|S_i)$). As detailed in Appendix D, we find no statistically significant difference in valuation across ambiguity types. In particular, the tendency to place higher value on signals from larger signal spaces was consistent regardless of ambiguity attitude.

These findings suggest that, unlike the patterns suggested by Halevy (2007), ambiguity neutrality does not predict adherence to expected utility theory in our setting. Instead, our results support the idea that signal evaluation in environments with structured uncertainty reflects a different psychological mechanism—namely, a preference for uncertainty reduction as captured by Shannon entropy, combined with reference-dependent evaluation. Thus, while ambiguity attitudes may explain some deviations from expected utility in classic compound lottery settings, they do not account for the distinctive signal preferences observed in our study.

6 Connections to Existing Literature

Our study contributes to several strands of work on information acquisition and valuation. In much of the signaling literature, the structure of the signal space is treated as secondary to its informativeness. Canonical models are typically framed with the signal space matching the action space for equilibrium analysis (Spence, 1973; Kamenica and Gentzkow, 2011; Heumann, 2020). Our results suggest that the size of the signal space may influence individuals' valuation of information, even when informativeness is held constant.

This pattern aligns with a growing body of work on non-instrumental information demand and curiosity. Behavioral and neuroscientific studies suggest that individuals derive utility from information itself, even when it has no impact on choices or outcomes (Bennett et al., 2016; Gottlieb and Oudeyer, 2018; Kobayashi and Hsu, 2019; Lau et al., 2020). Our entropy-based framework formalizes this motivation, showing that signals from larger spaces reduce more uncertainty and are therefore perceived as more valuable. Our findings also build on theories of reference-dependent preferences in information valuation. We show that individuals evaluate uncertainty reduction relative to context-dependent reference points, in line with behavioral theories of framing and reference dependence (Kőszegi and Rabin, 2007), and with psychological accounts of information valuation (Golman et al., 2017). Taken together, our findings underscore the role of context in shaping how uncertainty reduction is perceived and valued.

Finally, our results align with menu-dependent preference models, where the structure of the option set influences how individuals perceive and value alternatives (Masatlioglu et al., 2012). In our setting, a larger signal space appears to serve as a cue for increased informational richness, even when the actual informativeness is unchanged. Together, these connections highlight the need to account for non-instrumental motives—such as curiosity and reference-dependent reasoning—when modeling how individuals acquire and evaluate information.

7 Conclusion

This paper investigates whether the size of the signal space influences how individuals value informative signals when their informational value is held constant. We designed a controlled experiment to examine this question in two settings: the Signal Purchasing Decision (SPD), where subjects pay for signals, and the Lottery Purchasing Decision (LPD), where subjects pay for equivalent lotteries.

In the SPD, subjects exhibited a higher willingness to pay for signals from larger signal spaces, even though the signals provided the same informational value. In contrast, no such pattern emerged in the LPD. These findings suggest that preferences for signal space size are shaped not only by instrumental value of information but also by the context in which the information is acquired.

To account for this behavior, we develop a theoretical framework that incorporates non-instrumental motivations—particularly the desire to reduce uncertainty. Using Shannon's entropy, we formalize this as a preference for signals that resolve more uncertainty, even when they do not improve expected outcomes.

Our analysis considers a setting in which signals are drawn from a uniform distribution. When the distribution is highly skewed, however, receiving a signal from a larger signal space does not necessarily imply a greater reduction in uncertainty—for example, when many of the signals in the larger space are extremely unlikely to occur. Investigating how the distribution of signals interacts with signal space size in shaping individuals' willingness to pay is a promising direction for future research.

More broadly, there is room for further research on how the signal space influences information acquisition and decision-making. In our experiment, we limited the action space to binary choices and capped the number of possible signals at five to maintain parsimony and keep the design focused. Relaxing these assumptions—for example, by allowing richer action or signal spaces—may uncover further insights. We hope our study encourages future work on the role of signal space in shaping information demand and belief formation.

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A Predictions Following Signals

Table 11 shows subjects' prediction decisions after the signal stage. The majority of subjects followed the signal when their signal was informative (Box R or Box B). This suggests that the subjects comprehended the information structure of the experiments. In both studies, the chi-square test and Fisher's exact test indicate that the null hypothesis of random prediction by subjects can be rejected. (p-values < 0.001 for both studies.)

Table 11: Predictions following signals in the SPD and the LPD

	Predictions	Box R	Box B	Box G	No Signal
SPD	Red	16 (94.1%)	3 (15.8%)	12 (85.7%)	85 (65.9%)
	Blue	1 (5.9%)	16 (84.2%)	2 (14.3%)	44 (34.1%)
LPD	Red	37 (94.9%)	4 (11.1%)	8 (72.7%)	N/A
	Blue	2 (5.1%)	32 (88.9%)	3 (27.3%)	N/A
Chi-square test p-value = 0.000					

The purpose of Table 12 is to investigate whether the signal space size influences the prediction decisions. The correct decision rate is defined as whether the subject's prediction aligns with the signal suggested after receiving Box R or Box B as a signal. Results show that there is no correlation between the correct decision rate and the signal space size. (Chi-square test p-value and Fisher's exact test p-value are approximately 0.513 and 0.672, respectively).

Table 12: Correct decision rate with each signal

Signal Received	s_1	s_2	s_3	s_4	Total
Correct	9 (81.8%)	3 (100.0%)	11 (84.6%)	9 (100.0%)	32 (88.9%)
Incorrect	2 (18.2%)	0 (0.0%)	2 (15.4%)	0 (0.0%)	4 (11.1%)
Total	11	3	13	9	36
Chi-square test p-value = 0.513					

B Payoffs and Signal Space Size

This section examines whether the preference for larger signal spaces harms information buyers. Table 13 displays subjects' payoffs (in points) in both the SPD and the LPD. Note that profits were generally higher in the SPD due to the 100-point endowment.

In the SPD, the highest average profit was earned by subjects who played the simplest lottery (Lottery 1), suggesting that participants earned lower profits when choosing lotteries with larger signal spaces. However, this pattern did not emerge in the LPD, where payoffs did not systematically decrease with signal space size.

		SPD			LPD		
Lottery	|S|	Payoff	Std. Error	Number	Payoff	Std. Error	Number
1	2	160.9	7.1	48	71.6	6.2	32
2	3	141.6	7.5	50	80.0	4.5	43
3	4	140.9	7.0	46	67.0	6.2	40
4	5	142.0	8.2	35	72.8	5.4	43
Total		146.7	3.7	179	73.1	2.8	158

Table 13: Average payoffs by lottery in the SPD and the LPD

Table 14 reports the regression results to clarify whether and when signal space size affects the payoffs. Columns (1) and (3) estimate the direct effect of signal space size. The results show that only in the SPD does signal space size significantly affect payoffs: purchasing signals from larger signal spaces is associated with lower earnings.

Columns (2) and (4) examine the effect of playing the simplest lottery (Lottery 1). In the SPD, subjects who chose more complex lotteries (Lotteries 2–4) earned, on average, 19.4 points less than those who played Lottery 1 (F-test p-value = 0.0202). In contrast, Column (4) shows that this pattern disappears in the LPD.

These findings suggest that subjects tend to overvalue signals when the signal space is larger, leading them to overpay for information and ultimately earn lower

	Payoffs in SPD		Payoffs in LPD	
	(1)	(2)	(3)	(4)
Signal Space Size	-6.118*		-1.168	
	(3.380)		(2.543)	
Simplest Lottery		19.438**		-1.788
		(8.293)		(6.857)
Constant	161.231***	141.458***	76.114***	73.444***
	(9.003)	(4.326)	(6.954)	(3.136)
Observations	716	716	632	632
R-Squared	0.017	0.030	0.001	0.000

Notes: Robust standard errors clustered by individual in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14: Effect of signal space size on payoffs in the SPD and the LPD

payoffs.

C Predictions from Cumulative Prospect Theory

To examine whether Cumulative Prospect Theory (CPT) can account for the behavioral patterns observed in our experiment, we applied the standard functional form of CPT introduced by Kahneman and Tversky (1992). The utility of a lottery is given by:

$$U_{CPT} = \sum_{i=-m}^{n} \pi_i v(x_i), \tag{3}$$

where $v(x)$ is the value function and π_i are decision weights based on cumulative probabilities. The value function is defined as:

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0, \\ -\lambda(-x)^{\beta} & \text{if } x < 0, \end{cases} \tag{4}$$

and the decision weights for gains and losses are computed using:

$$w^{+}(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}, \quad w^{-}(p) = \frac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{1/\delta}}. \tag{5}$$

We used the parameter values estimated in Kahneman and Tversky (1992):

Table 15: Parameter values from Kahneman and Tversky (1992)

Parameter	Description	Value
α	curvature for gains	0.88
β	curvature for losses	0.88
λ	loss aversion	2.25[9]
γ	probability weighting (gains)	0.61
δ	probability weighting (losses)	0.69

We assumed the cost of acquiring a signal to be 20, corresponding to the expected value of information under risk neutrality. With these values, CPT predicts the following preference orderings in both the SPD and LPD:

$$V(S_1|L_1) \geq V(S_3|L_3) \geq V(S_4|L_4) \geq V(S_2|L_2), \tag{6}$$
$$V(L_1|S_1) \geq V(L_3|S_3) \geq V(L_4|S_4) \geq V(L_2|S_2).$$

These rankings remain consistent across contexts, as CPT evaluates information purely in terms of its instrumental value in shaping expected outcomes. This uniformity stands in contrast to our experimental findings.

[9] A meta-analysis by Brown et al. (2022) finds an average estimate of $\lambda = 1.97$. Using this alternative value does not change the predicted ranking.

D Measuring Ambiguity Attitudes

To assess whether individual ambiguity attitudes are associated with signal valuation patterns, we administered a canonical Ellsberg task (Ellsberg, 1961) after the main decision tasks.

Subjects chose between two pairs of options: A vs. B, and C vs. D, as shown in Table 16. Preferring A over B and D over C is typically interpreted as ambiguity aversion.

Options	
Option A	receiving 100 points if a blue ball is drawn.
Option B	receiving 100 points if a red ball is drawn.
Option C	receiving 100 points if a blue or yellow ball is drawn.
Option D	receiving 100 points if a red or yellow ball is drawn.

Table 16: Ellsberg questions

Ambiguity	SPD		LPD	
Attitude	Number	Percentage	Number	Percentage
Averse	72	40.2%	55	34.8%
Neutral	85	47.5%	84	53.2%
Seeking	22	12.3%	19	12.0%
Total	179	100.0%	158	100.0%

Table 17: Ambiguity attitudes

Table 17 and Table 18 respectively describe the ambiguity attitudes of subjects, and the values of $V(S_i|L_i)$ and $V(L_i|S_i)$ conditional on different ambiguity attitudes. The overall patterns of the willingness to pay for signals and lotteries remain consistent across different ambiguity attitudes. The F-tests' p-values indicate that there is no significant effect of ambiguity attitude on $V(S_i|L_i)$ or $V(L_i|S_i)$.

To formally examine these relationships, we estimate the following linear regres-

Attitude	$V(S_1\|L_1)$	$V(S_2\|L_2)$	$V(S_3\|L_3)$	$V(S_4\|L_4)$	$V(L_1\|S_1)$	$V(L_2\|S_2)$	$V(L_3\|S_3)$	$V(L_4\|S_4)$
Averse	22.8	23.8	24.4	29.9	55.7	47.7	49.5	55.8
Neutral	23.8	26.9	24.9	29.2	50.7	48.8	50.8	50.8
Seeking	25.5	28.7	26.5	31.4	54.2	52.9	55.8	52.2
Total	23.6	25.9	24.9	29.8	52.9	48.9	51.0	52.7
F-test p-value	0.8142				0.5988			

Table 18: The submitted values of $V(S_i|L_i)$ and $V(L_i|S_i)$ for different ambiguity attitudes

sion model:

$$y_{in} = \beta_0 + \beta_1 |S|_i + \beta_2 AmbNeutral_n + \beta_3 |S|_i * AmbNeutral_n + \epsilon_{in}. \tag{7}$$

Here, $y_{i,n}$ represents the value assigned to either p_i or V_i by individual n, while $AmbNeutral_n$ is a dummy variable that indicates whether individual n is ambiguity neutral or not. Standard errors are clustered by subject.

	$V(S_i\|L_i)$		$V(L_i\|S_i)$	
	(1)	(2)	(3)	(4)
Signal Space Size	1.934***	2.030***	0.160	0.077
	(0.395)	(0.551)	(0.502)	(0.727)
Ambiguity Neutrality		0.862		-2.698
		(3.326)		(3.607)
Signal Space Size × Ambiguity Neutrality		-0.203		0.156
		(0.792)		(1.006)
Constant	21.218***	20.809***	50.978***	52.412***
	(1.650)	(2.154)	(1.798)	(2.661)
Observations	716	716	632	632
R-Squared	0.010	0.010	0.000	0.003

Notes: Robust standard errors clustered by individual in parentheses. Columns (2) and (5) cannot include subject fixed effect because the ambiguity attitude is measured at the subject level *** p<0.01, ** p<0.05, * p<0.1

Table 19: The effect of the size of signal space and ambiguity neutrality on the value of the signal space and the lottery

The third row of Table 19 shows that preferences over signal space size are independent of ambiguity neutrality. This contrasts with the findings of Halevy (2007), who report a strong link between ambiguity neutrality and the simplification of compound lotteries.