Pre-Analysis Plan: Mental Models and Learning in Complex Environments

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1 Research Question and Hypotheses

1.1 Research Questions

Expectation plays a key role in economic decision-making. In various settings such as corporate ESG disclosure, central bank communication, and clinical trials reports, greater transparency is called for precisely because it can shape people's expectations that will eventually affect their economic behaviors.

Standard economic theories suggest that providing more information should improve subjective probability judgments. However, Esponda et al. (2024) found in a binary-state belief updating experiment that providing the underlying primitives of the data-generating process actually hinders participants' learning from sequential feedback.

Furthermore, Ba et al. (2025) documented that increasing the complexity of the information environment may "have a striking effect on belief updating": people underreact to information in simple two-state uniform-prior environments, but overreact in three-state uniform-prior environments.

Our experiment investigates whether the learning inefficiency induced by providing primitives, as documented by Esponda et al. (2024), generalizes to a three-state information environment with asymmetric priors.

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1.2 Experimental Design Overview

The experiment employs a 2×2 between-subjects design with four treatments that differ in the information environment. The first two treatments are replications of the binary-states experiment by Esponda et al. (2024), while the last two are their analogues with an additional state.

SP treatment (Simple environment with Primitives). Subjects are provided with the following messages:

- Of the 100 projects, there are 15 projects that are successes and 85 projects that are failures.
- The test result can be either *Positive* or *Negative* and has a reliability of 80 %. It means that:
  - If the project is a *Success*, the test result will be *Positive* with 80 % chance and the test result will be *Negative* with 20 % chance.
  - If the project is a *Failure*, the test result will be *Negative* with 80 % chance and the test result will be *Positive* with 20 % chance.

SNP treatment (Simple environment without Primitives). Subjects are provided with the following messages:

- Of the 100 projects, a certain number of them are successes and the remaining ones are failures. But we will not tell you how many of them are successes or how many are failures.
- The test result can be either *Positive* or *Negative* and has a reliability of R %. It means that:
  - If the project is a *Success*, the test result will be *Positive* with R % chance and the test result will be *Negative* with $(100 - R)$ % chance.
  - If the project is a *Failure*, the test result will be *Negative* with R % chance and the test result will be *Positive* with $(100 - R)$ % chance.
- The reliability R is a specific numbers between 0 and 100, but we will not tell you this number.

CP treatment (Complex environment with Primitives). Subjects are provided with the following messages:

- Of the 100 projects, there are 10 projects that are successes, 25 projects that are neutrals, and 65 projects that are failures.
  - If the project is a *Success*, the test result will be *Positive* with 80 % chance and the test result will be *Negative* with 20 % chance.
  - If the project is a *Neutral*, the test result will be *Positive* with 45 % chance and the test result will be *Negative* with 55 % chance.
  - If the project is a *Failure*, the test result will be *Positive* with 15 % chance and the test result will be *Negative* with 85 % chance.

CNP treatment (Complex environment without Primitives). Subjects are provided with the following messages:

- Of the 100 projects, a certain number of them are successes, a certain number of them are neutrals, and the remaining ones are failures. But we will not tell you how many of them are successes, how many are neutrals, or how many are failures.
  - If the project is a *Success*, the test result will be *Positive* with R_3 % chance and the test result will be *Negative* with $(100 - R_3)$ % chance.
  - If the project is a *Neutral*, the test result will be *Positive* with R_2 % chance and the test result will be *Negative* with $(100 - R_2)$ % chance.
  - If the project is a *Failure*, the test result will be *Positive* with R_1 % chance and the test result will be *Negative* with $(100 - R_1)$ % chance.
- $R_1 < R_2 < R_3$ are specific numbers between 0 and 100, but we will not tell you the exact numbers.

Table 1 briefly summarizes the experimental design. In the main task, subjects in the CP and CNP treatments will be asked to assess the probabilities that a project is a *Success*, a *Neutral*, or a *Failure* for each possible test result (*Positive* or *Negative*); subjects in the SP and SNP treatments will be asked to assess the probabilities that a project is a *Success* or a *Failure* for each possible test result (*Positive* or *Negative*). In Stage 5, we will ask subjects to recall the feedback they received during rounds 1–200 of the main task.

Subjects will not interact with each other at any point during the experiment.

Table 1: **Experimental Design**

Stage	Round	Task
1	001	**Tutorial.** Introduce the BDM method and strategy method using simple examples.
2	001	**The Main task.**
3	002–100	**Learning:** Repetition of the main task. Belief elicited at every single round.
4	101–200	**Learning:** Repetition of the main task. Belief elicited at every 10th round.
5	201	**Recollection of feedback.**
6	202	**Summary tables.** True feedback statistics revealed. Main task.
7	203	**Summary tables.** 1000-round statistics (200 real + 800 simulated) revealed. Main task.
8	204	**Summary tables.** Frequency derived from the 1000-round statistics revealed. Main task.
9	205	**Transfer of learning.** Primitives changed. Main task.
		Survey.

1.3 Hypotheses

Hypothesis 1 (Initial response). People exhibit base-rate neglect. The elicited posterior beliefs systematically deviate from the normative Bayesian benchmarks. Furthermore, certain subjects in the *Primitives* treatments (SP and CP) manifest perfect base-rate neglect in the initial round of the experiment. They completely ignore the base rates and form their posterior beliefs solely based on the test reliability.

Specifically, there are some subjects in the SP treatment who report:

$$\Pr(\text{Success} \mid \text{Positive}) = 0.80 \quad \Pr(\text{Success} \mid \text{Negative}) = 0.20$$
$$\Pr(\text{Failure} \mid \text{Positive}) = 0.20 \quad \Pr(\text{Failure} \mid \text{Negative}) = 0.80$$

Similarly, in the CP treatment, some subjects report the following probability judgments:

$$\begin{array}{ll} \Pr(\text{Success} \mid \text{Positive}) \approx 0.57 & \Pr(\text{Success} \mid \text{Negative}) \approx 0.13 \\ \Pr(\text{Neutral} \mid \text{Positive}) \approx 0.32 & \Pr(\text{Neutral} \mid \text{Negative}) \approx 0.34 \\ \Pr(\text{Failure} \mid \text{Positive}) \approx 0.11 & \Pr(\text{Failure} \mid \text{Negative}) \approx 0.53 \end{array}$$

Intuitively, the first estimates that come to a pBRN-type subject's mind upon seeing a *Positive* test result are: $\Pr(\textit{Success} \mid \textit{Positive}) = 80\,\%$, $\Pr(\textit{Neutral} \mid \textit{Positive}) = 45\,\%$, and $\Pr(\textit{Failure} \mid \textit{Positive}) = 15\,\%$. However, the subject immediately realizes that these three probabilities do not sum to 100 %. Hence, he adjusts the values proportionally to satisfy the normalization condition $\Pr(\textit{Success} \mid \textit{Positive}) + \Pr(\textit{Neutral} \mid \textit{Positive}) + \Pr(\textit{Failure} \mid \textit{Positive}) = 100\,\%$, yielding approximate final estimates of 57 %, 32 %, and 11 %, respectively. The same logic applies when the test result is *Negative*, yielding approximate final estimates of 13 %, 34 %, and 53 %, respectively.

Hypothesis 2 (Learning from feedback). Initial misconceptions hinder learning from feedback. After 200 rounds of belief-updating tasks, the beliefs of subjects in treatments without primitives (SNP and CNP) are on average closer to the normative Bayesian benchmark than those in the corresponding treatments with primitives (SP and CP), respectively.

Hypothesis 3 (Complexity matters). Increasing the complexity of the information environment has a statistically significant effect on belief updating. Specifically, the difference in beliefs between CP and CNP (i.e., the effect of providing primitives in a complex environment) differs significantly from the difference between SP and SNP (i.e., the effect of providing primitives in a simple environment).

2 Sample Selection and Relevant Moderators

2.1 Sample Size

We will run 3 sessions per treatment with 20 subjects per session, yielding 60 subjects per treatment and a total sample size of 240. With 205 rounds per session, this generates 12,300 subject-round observations per treatment.

2.2 Population and Recruitment

Subjects will be recruited from the university student population using standard experimental economics recruitment procedures. Individuals who have participated in similar belief-updating experiments within the past 12 months will be excluded to avoid contamination from prior exposure to comparable tasks. We will recruit 22 participants for each session in case of non-attendance. If more than 20 subjects show up (e.g., all 22 recruited participants attend on time), the additional subjects will still be allowed to participate. Hence, the actual number of participants per session equals the number of attendees.

2.3 Randomization

Treatment assignment occurs at the session level (between-subjects).

2.4 Individual-Level Moderators

There is a post-experiment survey eliciting several individual characteristics:

- Gender
- Year of study
- Major category (science/technology, economics/management, other)
- Completed a course in probability theory

3 Experimental Integrity

3.1 Data Cleaning

If a subject disconnects or fails to complete the procedure, her data will be excluded from the analysis.

3.2 Comprehension Checks

Subjects must correctly answer all comprehension questions before proceeding to Stage 2 of the experiment. The comprehension quiz tests understanding of: (i) the project composition (the numbers of *Success*, *Neutral* and *Failure* projects); (ii) the signaling mechanism (the conditional probabilities of generating *Positive* and *Negative* signal realizations).

4 Data Sources and Variable Construction

4.1 Data Generated

The primary data collected is shown in Table 2.

Table 2: Primary Outcome Variables

Variable	Description
subject_id	Consecutive id across sessions and treatments
subject_code	Unique participant code
session	Session code
treatment	Treatment group (CP / CNP / SP / SNP)
Round	Round number (1 to 205)
stage	Experiment stage (1 to 9)
state	True state drawn (*Success* / *Neutral* / *Failure*)
signal	True signal realization (*Positive* / *Negative*)
Primitives	Dummy, SP/CP = 1, SNP/CNP = 0
Complex	Dummy, CP/CNP = 1, SP/SNP = 0
Bpossuc	Belief elicited in each round, Pr(*Success* | *Positive*)
Bposneu	Belief elicited in each round, Pr(*Neutral* | *Positive*)
Bposfail	Belief elicited in each round, Pr(*Failure* | *Positive*)
Bnegsuc	Belief elicited in each round, Pr(*Success* | *Negative*)
Bnegneu	Belief elicited in each round, Pr(*Neutral* | *Negative*)
Bnegfail	Belief elicited in each round, Pr(*Failure* | *Negative*)
Npossuc	Cumulative feedback count: (*Positive*,*Success*)
Nposneu	Cumulative feedback count: (*Positive*,*Neutral*)
Nposfail	Cumulative feedback count: (*Positive*,*Failure*)
Nnegsuc	Cumulative feedback count: (*Negative*, *Success*)
Nnegneu	Cumulative feedback count: (*Negative*, *Neutral*)
Nnegfail	Cumulative feedback count: (*Negative*, *Failure*)
ReNpossuc	Recall count (Stage 5): (*Positive*,*Success*)
ReNposneu	Recall count (Stage 5): (*Positive*,*Neutral*)
ReNposfail	Recall count (Stage 5): (*Positive*,*Failure*)
ReNnegsuc	Recall count (Stage 5): (*Negative*, *Success*)
ReNnegneu	Recall count (Stage 5): (*Negative*, *Neutral*)
ReNnegfail	Recall count (Stage 5): (*Negative*, *Failure*)
final_payoff	Final payoff in CNY (base 40 + BDM bonus)

4.2 Treatment Assignment and Randomization Details

Total payment. The experiment consists of 9 stages, one of which will be randomly selected for payment at the end of the experiment. In the part that is randomly selected for payment a subject can make either 100 CNY or 0 CNY. In addition to their earnings from the experiment, subjects will also receive a show-up fee of 40 CNY for participating in the experiment. This means that at the end of the experiment a subject will receive a payment of 140 CNY (if in the randomly selected part she made 100 CNY) or 40 CNY (if in the randomly selected part she made 0 CNY).

Payment for probability judgments (except stage 5). In every question, a subject submits a judgment about the probabilities that a set of events will occur. The interface will randomly select an event and denote the submitted probability for that event as X (in percent). Then the interface will draw a number Y from 0 to 100, with each number being equally likely. The values of X and Y, together with whether the selected event actually occurs, determine the probability that the subject wins 100 CNY (otherwise 0 CNY).

- If $Y \geq X$, the subject receives 100 CNY with probability $Y\,\%$ and 0 CNY otherwise;
- If $Y < X$, the subject receives 100 CNY when the selected event is realized and 0 CNY otherwise.

This mechanism is *Incentive-Compatible*: a subject maximizes expected payment by setting X equal to their true subjective probability.

Payment for Stage 5. If stage 5 is selected for payment, the interface will randomly select one of the entries on the table. If the number a subject reported for this entry is within plus or minus 5 of the actual number she experienced during the 200 rounds, she will receive 100 CNY; otherwise, she will receive 0 CNY.

5 Statistical Approach

5.1 Descriptive Statistics

- We will report by treatment the mean, mode and median beliefs elicited in rounds 1, 50, 100, and 200, along with the recollection of feedback statistics in Stage 5.
- We will report the proportion of pBRN-type subjects in treatments SP and CP at round 001.
- We will illustrate graphically the evolution of beliefs at the aggregate level across all rounds.

5.2 Testing Hypothesis 2

In order to test Hypothesis 2, we will analyze the subjective beliefs elicited in selected rounds of the experiment (i.e., rounds 1, 50, 100, and 200). We will conduct this analysis separately for the simple-environment treatments (SP and SNP) and the complex-environment treatments (CP and CNP). For each selected round t, we will separately estimate the following two equations by OLS:

$$Y_{1i} = \alpha_{10} + \alpha_{11}\text{Primitives}_i + \varepsilon_{1i} \tag{1}$$

$$Y_{2i} = \alpha_{20} + \alpha_{21}\text{Primitives}_i + \varepsilon_{2i} \tag{2}$$

where Primitives_i is the treatment dummy variable; Y_{1i} and Y_{2i} denote the absolute value of the distance between the submitted beliefs and the Bayesian benchmarks conditional on a *Positive* and a *Negative* test result, respectively.

In the simple 2-state environment, we will restrict the dependent-variable pair to $(Y_{1i}, Y_{2i}) = (|\text{Bpossuc}_{it} - \text{Bpossuc}^{Bay}|, |\text{Bnegsuc}_{it} - \text{Bnegsuc}^{Bay}|)$. This is because, for each test result, the subjective probabilities of *Success* and *Failure* sum to 100 (i.e., $\text{Bpossuc}_{it} + \text{Bposfail}_{it} = 100$ and $\text{Bnegsuc}_{it} + \text{Bnegfail}_{it} = 100$). Consequently, the absolute distances for *Failure* are identical to those for *Success*, making a separate analysis of the *Failure* pair redundant.

In the complex 3-state environment, we will estimate the same two equations three times, once for each of the following pairs: $(|\text{Bpossuc}_{it} - \text{Bpossuc}^{Bay}|, |\text{Bnegsuc}_{it} - \text{Bnegsuc}^{Bay}|)$, $(|\text{Bposneu}_{it} - \text{Bposneu}^{Bay}|, |\text{Bnegneu}_{it} - \text{Bnegneu}^{Bay}|)$, and $(|\text{Bposfail}_{it} - \text{Bposfail}^{Bay}|, |\text{Bnegfail}_{it} - \text{Bnegfail}^{Bay}|)$. (See Table 2.)

Because equations (1) and (2) share the same set of regressors, the OLS coefficient estimates are numerically identical to those from a seemingly unrelated regression (SUR) system (Zellner, 1962).

Since a subject forms the posterior beliefs conditional on a *Positive* and a *Negative* test result simultaneously, the error terms ε_{1i} and ε_{2i} may be correlated across equations. To account for this correlation and to compare coefficients between the two equations, we will obtain the joint covariance matrix of the estimators via SUR (i.e., treat the two equations as a system) and then conduct Wald tests for the null hypotheses $H_0 : \alpha_{10} = \alpha_{20}$ and $H_0 : \alpha_{11} = \alpha_{21}$. These tests will be performed separately for the simple environment (using the *Success* pair) and for each of the three pairs in the complex environment.

5.3 Testing Hypothesis 3

In order to test Hypothesis 3, we will implement OLS regressions using three categories of dependent variables that will be constructed out of the data from all four treatments. Analogous to Section 5.2, in each of the selected rounds (i.e., rounds 1, 50, 100, and 200), we will separately estimate the following two equations:

$$Y_{3i} = \alpha_{30} + \alpha_{31}\text{Primitives}_i + \alpha_{32}\text{Complex}_i + \alpha_{33}(\text{Primitives}_i \times \text{Complex}_i) + \varepsilon_{3i} \tag{3}$$

$$Y_{4i} = \alpha_{40} + \alpha_{41}\text{Primitives}_i + \alpha_{42}\text{Complex}_i + \alpha_{43}(\text{Primitives}_i \times \text{Complex}_i) + \varepsilon_{4i} \tag{4}$$

where Primitives_i and Complex_i are treatment dummies.

Again, because the two error terms may be correlated, we will apply the same SUR procedure after estimating equations (3) and (4) separately by OLS, and then test H_0 : $\alpha_{3k} = \alpha_{4k}\,(k = 0, 1, 2, 3)$ (i.e., separately for the intercept, Primitives, Complex, and the interaction term) using Wald tests.

The dependent variables in the first category are the absolute values of the distance between the submitted beliefs and the Bayesian benchmarks, as in Section 5.2. Specifically, (Y_{3i}, Y_{4i}) is either $(|\text{Bpossuc}_{it} - \text{Bpossuc}^{Bay}|, |\text{Bnegsuc}_{it} - \text{Bnegsuc}^{Bay}|)$ or $(|\text{Bposfail}_{it} - \text{Bposfail}^{Bay}|, |\text{Bnegfail}_{it} - \text{Bnegfail}^{Bay}|)$. (The subjects in SP and SNP treatments do not report Bposneu_{it} and Bnegneu_{it}.)

Second, in order to improve the comparability of the data between the *Simple* and *Complex* environments, we assign a numerical value $\omega \in (0, 1)$ to each of the possible states, *Success*, *Neutral*, and *Failure*, and then calculate the subjective conditional expectation of the resulting random variable. Following Ba et al. (2025), let $\omega_k = \pi(+|\omega_k)$, where "+" denotes a *Positive* test result. For example, the numerical value assigned to state *Success* equals the probability of generating a *Positive* test result when the selected project is a *Success*. Further details of the information environments are shown in Table 3, where "−" denotes a *Negative* test result, and K is the number of possible states. Now we can define the expected state as follows:

$$\hat{\mathbb{E}}_{it}[\omega|s] = \sum_{k=1}^{K} \omega_k p_{it}(\omega_k|s), \quad s \in \{+, -\}$$

where $p_{it}(\omega_k|s)$ is the reported subjective posterior probability of state ω_k conditional on test result s in round t. We will run OLS regressions using $(Y_{3i}, Y_{4i}) = (\hat{\mathbb{E}}_{it}[\omega|+], \hat{\mathbb{E}}_{it}[\omega|-])$ as the dependent-variable pair.

Table 3: **Information Environment Parameters**

K	$\omega \in \Omega$	$\pi(+\|\omega)$	$\pi(-\|\omega)$	$p_0(\omega)$
$K = 2$ (Simple)	$\omega_2 = 0.80$ (Success)	0.80	0.20	0.15
	$\omega_1 = 0.20$ (Failure)	0.20	0.80	0.85
$K = 3$ (Complex)	$\omega_3 = 0.80$ (Success)	0.80	0.20	0.10
	$\omega_2 = 0.45$ (Neutral)	0.45	0.55	0.25
	$\omega_1 = 0.15$ (Failure)	0.15	0.85	0.65

Finally, following Ba et al. (2025), we will measure the distortion from normative Bayesian benchmarks by comparing subjective and objective movements in beliefs in terms of the expected state. Define

$$\mathrm{OR}_{it}(s) := \frac{\hat{\mathbb{E}}_{it}[\omega|s] - \mathbb{E}_B[\omega|s]}{\mathbb{E}_B[\omega|s] - \mathbb{E}_0[\omega]}, \quad s \in \{+, -\}$$

where $\hat{\mathbb{E}}_{it}[\omega|s]$ is subject i's subjective expected state following test result s in round t; $\mathbb{E}_B[\omega|s]$ is the objective (Bayesian) expected state and $\mathbb{E}_0[\omega]$ is the expected state based on prior probabilities. A value of $\mathrm{OR}_{it}(s) > 0$ indicates overreaction; a value of $\mathrm{OR}_{it}(s) \in [-1, 0)$ indicates underreaction; a value of $\mathrm{OR}_{it}(s) < -1$ indicates reverse reaction. We will illustrate graphically the evolution of $\mathrm{OR}_{it}(s)$ at the aggregate level across rounds 1–200, and run OLS regressions in each of the selected rounds (i.e., rounds 1, 50, 100, and 200) using $(Y_{3i}, Y_{4i}) = (\mathrm{OR}_{it}(+), \mathrm{OR}_{it}(-))$ as the dependent-variable pair.

5.4 Power Analysis

We conducted a power analysis using SPSSAU[1] to evaluate the statistical power for detecting coefficients in the regression model above. The analysis assumed a two-tailed test with a Type I error rate of 0.05, and the anticipated effect size for the interaction coefficient was specified as a standardized regression coefficient of 0.2, tested against a null value of 0. The overall model R^2 was set to 0.3.

For equations (1) and (2), the sample size is 120. Under these parameters, the computed Type II error probability was 0.262, yielding a statistical power of 0.738. Hence, our study has approximately 73.8 % power to detect a non-zero coefficient in these models.

[1]The SPSSAU project (2026). SPSSAU. (Version 26.0) [Online Application Software]. Retrieved from https://www.spssau.com.

For equations (3) and (4), the sample size is 240. Under these parameters, the computed Type II error probability was 0.042, yielding a statistical power of 0.958. It indicates that, given the specified effect size and sample size, our study has approximately 95.8 % power to detect a non-zero coefficient at the 0.05 significance level.

6 Ethical

6.1 Data Governance and Management

All data will be stored on encrypted, password-protected servers maintained by the research team. Personal identifiers (names, student IDs) will be stripped upon session completion and replaced with anonymous subject codes. Only the principal investigators will have access to the crosswalk between identifiers and subject codes. De-identified data will be archived and made publicly available upon publication, in accordance with journal data policy requirements.

6.2 Ethical Principles

Beneficence. The experiment poses minimal risk. Subjects earn money for their time and efforts, and potential discomfort is limited to the cognitive effort of making judgments in a 200-round procedure. Expected total earnings (100 CNY for 90 minutes) exceed the local hourly wage for student jobs.

Respect for persons. Participation is fully voluntary. Subjects may withdraw at any time and will receive their show-up fee regardless. Full debriefing is available upon request after the session.

Justice. Subjects are recruited equitably from the university population using standardized recruitment procedures. No targeting of vulnerable populations.

6.3 Statement on Deception

This experiment involves no deception. All instructions are truthful, random draws are genuinely random, and payoffs are calculated exactly as explained to participants.

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