Discussion Paper Series

IZA DP No. 18834

July 2026

Choosing Complexity: Cognitive Ability, Overconfidence, and Task Choice

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ISSN: 2365-9793

IZA DP No. 18834 July 2026

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Abstract

Workers and organizations routinely choose the complexity of tasks that they undertake. We study how cognitive ability and overconfidence shape this choice of task complexity, both theoretically and experimentally. Consistent with our model, we find that more cognitively able individuals choose more complex tasks. Conditional on cognitive ability, we find that more overconfident individuals also choose more complex tasks. About 80% of subjects pick their payoff-maximizing task, and higher cognitive ability predicts more efficient choices of task complexity. But errors are strikingly one-sided: nearly all who fail to choose optimally pick tasks that are too complex. Our findings suggest that organizations should pair task menus and incentives for choosing more complex tasks with information and feedback that help workers assess their ability and probability of success. This preserves the benefits of self-selection while reducing costly overreach.

JEL classification

C91, D03, D83, D91, J24

Keywords

cognitive ability, complexity, task choice, choice efficiency, overconfidence, experiment

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* We are grateful for helpful comments from seminar participants and in private conversations. We thank the Vernon Smith Experimental Economics Laboratory at Purdue University for hosting our experiment and the Daniels School of Business for providing internal funding.

I Introduction

Workers and organizations routinely choose how complex a task to undertake, and the choice has real consequences for pay and productivity. Simpler tasks are more likely to succeed, while more complex tasks offer higher rewards when they do succeed. A manager may choose between a simple and a complex pricing strategy. The complex strategy delivers higher profits when executed well, but it has more moving parts and is easier to misapply. A lawyer may choose between routine small cases and high-stakes cases. High-stakes cases are harder to win, but they bring larger rewards when won.

Cognitive ability is a powerful predictor of labor-market outcomes and of the quality of economic decisions (Burks et al., 2009; Fe et al., 2022; Deming and Silliman, 2025). Field evidence links managerial ability to performance in complex environments (Goldfarb and Xiao, 2011; Hortaçsu et al., 2019; Han et al., 2024), and lab evidence shows that cognitive ability affects strategic sophistication (Carpenter et al., 2013; Gill and Prowse, 2016; Gill et al., 2025). Yet when workers can choose how complex a task to undertake, we know little about who selects into more complex tasks, whether those choices are well calibrated to their cognitive ability, and how beliefs about cognitive ability shape choices of task complexity.

In this paper, we provide theoretical and experimental evidence on how cognitive ability and overconfidence shape choice of task complexity. We address three research questions. First, do more cognitively able people choose more complex tasks? Second, conditional on cognitive ability, do more overconfident people choose more complex tasks? Third, do more cognitively able people choose their optimal task more often?

We develop a model in which a decision-maker chooses how complex a task to attempt. The probability of making a mistake depends on her cognitive ability and on the complexity of the chosen task. Higher cognitive ability lowers the mistake probability at every level of complexity, and higher complexity raises the mistake probability at every level of cognitive ability. The success payment (that is, the reward for success) rises with the complexity of the chosen task, while the failure payment is constant. The decision-maker therefore trades off a higher success payment on a more complex task against a higher mistake probability on that task. The model directly yields our first hypothesis: more cognitively able individuals choose more complex tasks.

We then augment the model with two behavioral assumptions motivated by prior empirical work, and each assumption delivers a further hypothesis. First, we assume that the decision-maker's belief about her own cognitive ability helps to shape her choice. This assumption yields our second hypothesis: more overconfident individuals choose more complex tasks. Hypothesis 2 is motivated by prior evidence, specifically prior work that links overconfidence and decision making. For example, Camerer and Lovallo (1999) and Larkin and Leider (2012) document that overconfidence predicts, respectively, excess entry into competitions and the selection of riskier incentive schemes.[1] Second, we assume that identifying the optimal level of task complexity is itself cognitively demanding. This assumption yields our third hypothesis: more cognitively able individuals choose their payoff-maximizing task more frequently. Hypothesis 3 is also motivated by prior evidence, specifically prior work that links cognition and the quality of decisions. For example, Agarwal and Mazumder (2013) and Ambuehl et al. (2022) document that cognitive ability and deliberative competence, respectively, link to the quality of financial decisions.

We test these hypotheses in a pre-registered laboratory experiment.[2] To bring the model to the laboratory, we construct two pairs of tasks adapted from Oprea (2020). In each pair, the subject chooses between a less complex task and a more complex task to implement. As in the model, the success payment rises with the complexity of the chosen task, while the failure payment is constant. We use rule implementation tasks from Oprea (2020), in which subjects implement finite automata of varying complexity. We measure cognitive ability using the 11-item matrix-reasoning test from the International Cognitive Ability Resource (Dworak et al., 2021). Matrix reasoning is a leading measure of fluid intelligence and has been used in economics by, for example, Gill and Prowse (2016) and Proto et al. (2019, 2022). We elicit each subject's belief about her own score in the matrix-reasoning test and define overconfidence as the difference between her belief and her score.[3]

All three hypotheses are supported by the data. From the choice between the less complex and the more complex task in each pair of tasks, we obtain our first two results. First,

[1] In Köszegi (2006)'s theoretical model, overconfidence drives the choice of more ambitious tasks via self-image concerns.

[2] The experiment was pre-registered on the Open Science Framework. We pre-registered our model, experimental design, and hypotheses, including the definition of overconfidence.

[3] We use 'overconfidence' in the sense of overestimation of one's own cognitive ability, following the taxonomy in Moore and Healy (2008). Like us, Tekleselassie et al. (2025) use a matrix-reasoning test and elicit subjects' beliefs about their own scores to measure overconfidence, and find an asymmetry: underconfident job seekers intensify search after feedback about their relative ability, while overconfident ones do not adjust their behavior.

higher cognitive ability predicts the choice of more complex tasks. Second, conditional on cognitive ability, higher overconfidence also predicts the choice of more complex tasks. Given that each subject attempts only the task she chooses, evaluating the optimality of that choice raises a selection problem. We therefore structurally estimate a model that accounts for endogenous selection, derive subjects' task-specific success probabilities, and use these estimates to identify each subject's optimal task. We find that about 80% of subjects choose optimally. More cognitively able subjects make more efficient choices of task complexity, and among those who fail to choose optimally, nearly all are undercautious, choosing the more complex task when the less complex task had a higher expected payoff. We also find that cognitive ability predicts realized earnings, as implied by our model.

Our primary contribution is to the literature on choice of task complexity. We study a setting in which subjects choose between two tasks that are both complex but differ in complexity and in the payment conditional on success. This design creates a direct tradeoff: the more complex task offers a higher success payment, but is expected to have a lower success probability. We link this tradeoff to measured cognitive ability and overconfidence, and show that both predict selection into the more complex task. Oprea (2020) measures task complexity using elicited willingness to pay to avoid a complex task in favor of a zero-complexity task (typing the same letter repeatedly), mistake rates, and implementation time, and finds that all three measures are influenced by cognitive ability. However, Oprea (2020) does not study choice among tasks of varying levels of complexity with a tradeoff between success probability and success payment. Related experiments (e.g., Niederle and Yestrumskas, 2008; Ou and Pan, 2021) study choice between a hard, higher-paid task and an easy, lower-paid task, focusing on gender differences in task choice. However, they do not focus on how cognitive ability affects this process. Our paper instead connects cognitive ability and overconfidence to choice of task complexity and further explores the optimality of task choice.[4]

Our second contribution is to the literature on cognitive ability and decision making

[4]Other work considers choice of complexity without focusing on the link to cognitive ability or overconfidence. Examples include choice of: decision-making procedures (e.g., Banovetz and Oprea, 2023; Kendall and Oprea, 2024); strategies in games (e.g., Romero and Rosokha, 2018, 2019; Salant and Spenkuch, 2026); choice sets or lotteries (e.g., Sonsino et al., 2002; Burton and Rigby, 2012; Moffatt et al., 2015); and disclosures or policies (e.g., Jin et al., 2022; Foarta and Morelli, 2025). Closest to our angle, Carvalho and Silverman (2024) study how a composite decision-making skill measure (based on numeracy, financial literacy, and consistency with GARP) predicts choice between a complex portfolio and a simple outside option.

in complex settings. We link cognitive ability to the optimality of task choice.[5] Because we observe each subject's task success or failure only for the task she chooses, we estimate subject-specific success probabilities using a model that accounts for endogenous selection. This allows us to identify each subject's payoff-maximizing task and measure the efficiency of her task choice. We find that cognitive ability predicts choice efficiency and earnings. Related papers connect cognitive ability to errors in complex decisions. Guan et al. (2025) study information demand through incentivized rankings of information structures. They find that subjects sometimes rank less instrumentally valuable structures above more valuable alternatives, and that cognitive ability predicts the optimality of these rankings. Brocas et al. (2019) find that working-memory and IQ scores correlate with GARP consistency in complex bundle choices involving three distinct goods, but not in simpler bundle choices involving only two goods. Relative to these studies, our paper examines the question of whether cognitive ability shapes the optimality of subjects' complexity choices.[6]

To briefly summarize, we find that: (i) cognitive ability and overconfidence both predict the choice of more complex tasks; (ii) about 80% of subjects choose optimally; (iii) more cognitively able subjects choose task complexity more efficiently; and (iv) when subjects err, they tend to overreach, mistakenly choosing the more complex task.

Our findings suggest that organizations and managers should actively design task menus, incentives for choosing more complex tasks, and feedback structures to account for (i) how workers choose task complexity and sometimes overreach by choosing tasks that are too complex, and (ii) how workers' task choices link to both their cognitive ability and confidence. In our setting, self-selection in task complexity often works: about 80% of subjects choose their payoff-maximizing task. At the same time, the mistakes are asymmetric. When subjects fail to choose optimally, they almost always choose the

[5] Cognitive ability is also associated with strategic behavior and sophistication in environments where subjects do not choose task complexity (e.g., Burks et al., 2009; Carpenter et al., 2013; Fehr and Huck, 2016; Gill and Prowse, 2016; Proto et al., 2019; Lambrecht et al., 2024; Gill et al., 2025; Gill and Rosokha, 2026).

[6] A broader literature studies how complexity affects decisions in various settings, such as lottery choice and the evaluation of risky prospects (e.g., Huck and Weizsäcker, 1999; Mador et al., 2000; Oprea, 2024); Bayesian updating (e.g., Charness and Levin, 2005); intertemporal choice (e.g., Enke et al., 2025); contingent reasoning (e.g., Park, 2025); effort provision (e.g., Abeler et al., 2025); strategic interactions (e.g., Devetag and Warglien, 2008; Gill and Prowse, 2023; Zhou and Raymond, 2024); and subjective perceptions of complexity (e.g., Agranov et al., 2025). See also Gabaix and Graeber (2024) for a general framework for the complexity of economic decisions.

more complex task when the less complex task has the higher expected payoff. This pattern maps naturally to workplaces in which employees volunteer for stretch projects, take on high-stakes client accounts, apply for promotion into more complex roles, or choose between narrower and more complex analytical assignments. Each case involves a choice of task complexity: the organization may benefit when able workers choose more complex tasks, because those tasks are more valuable when completed successfully. At the same time, workers may not have accurate beliefs about their own ability or about their probability of success on tasks. The implication is therefore not that organizations should remove ambitious options, but that they should design task menus carefully. Rewards for completing more complex tasks can help attract workers who are able to perform them, but they may also encourage overambitious workers to choose tasks for which the expected payoff is lower. Organizations and managers can respond by pairing the choice of more complex tasks with clear information and feedback: historical success rates for comparable tasks, low-stakes trial assignments before full responsibility, decision aids that make the payoff tradeoff salient, and post-project reviews that distinguish poor task choice from poor task execution. These features can help preserve the benefits of self-selection while helping workers learn when ambition is productive, when a more complex task is worth attempting, and when overconfidence might push them to be too ambitious.

The paper proceeds as follows. Section II presents the model. Section III describes the experimental design. Section IV develops the hypotheses. Section V tests the hypotheses. Section VI concludes.

II Model

We consider a model in which the probability of making a mistake in a task is determined by two factors: task complexity and the decision-maker's cognitive ability. The mistake probability depends on task complexity and cognitive ability in two intuitive ways.

- The mistake probability *increases* with task complexity. For any given level of cognitive ability, implementing a more complex task is more likely to produce an error.

- The mistake probability *decreases* with cognitive ability. For any given task, a more cognitively able decision-maker is less likely to make a mistake.

Let a_i denote the cognitive ability of decision-maker i and c_t denote the complexity level of task t. A greater a_i represents higher cognitive ability, while a greater c_t represents a higher complexity level. $P_m(a_i, c_t)$ denotes the probability that decision-maker i makes a mistake when implementing task t. The functional form should satisfy the following requirements:

(1) $\frac{\partial P_m(a_i,c_t)}{\partial c_t} > 0$: The mistake probability *increases* with the complexity of the task.

(2) $\frac{\partial P_m(a_i,c_t)}{\partial a_i} < 0$: The mistake probability *decreases* with the decision-maker's cognitive ability.

II.A Mistake Probability Function

We use the following functional form of the probability of making a mistake, $P_m(a_i, c_t)$:

$$P_m(a_i, c_t) = \alpha + \beta_1 a_i + \beta_2 c_t + \beta_3 a_i c_t \tag{1}$$

where α is a constant term. β_1, β_2, and β_3 are coefficients that quantify the impact of the decision-maker's cognitive ability (a_i) and the task's complexity (c_t). Without loss of generality, a_i and c_t are both normalized to $[0, 1]$. We impose the following restrictions:

A-1. $\frac{\partial P_m}{\partial c_t} = \beta_2 + \beta_3 a_i > 0, \ \forall a_i \in [0, 1]$. This assumption ensures that an increase in task complexity c_t increases the mistake probability, for any given cognitive ability.

A-2. $\frac{\partial P_m}{\partial a_i} = \beta_1 + \beta_3 c_t < 0, \ \forall c_t \in [0, 1]$. This assumption ensures that an increase in cognitive ability a_i decreases the mistake probability, for any given task complexity.

A-3. $\frac{\partial^2 P_m(a_i,c_t)}{\partial c_t \partial a_i} = \beta_3 \leq 0$. This assumption ensures that task complexity has a weakly smaller effect on the mistake probability of a more cognitively able decision-maker. This assumption is a sufficient but not necessary condition for Propositions 1 and 2, which continue to hold when β_3 is not too positive.

A-4. Probability bounds: $P_m(a_i, c_t) \in [0, 1], \ \forall (a_i, c_t) \in [0, 1]^2$.

We estimate the model freely to verify these restrictions, and all the restrictions are satisfied. See Appendix A.4 for details.

II.B Optimal Task Complexity and Cognitive Ability

Consider the maximization problem in which the decision-maker chooses a task t with complexity level $c_t \in [0,1]$ to maximize her expected payoff. The decision-maker receives a success payment $w_H(c_t)$ if she successfully implements the task and a failure payment w_L if she makes a mistake. $w_H(c_t)$ increases with task complexity, while w_L remains constant:

$$w_H(c_t) = w_L + k \cdot c_t \tag{2}$$

where $k > 0$ indicates the rate at which the success payment increases with complexity.

The decision-maker's objective is to choose task complexity to maximize her expected payoff $\pi(a_i, c_t)$:

$$\begin{aligned}
\max_{c_t \in [0,1]} \quad \pi(a_i, c_t) &= P_m(a_i, c_t) \cdot w_L + \big(1 - P_m(a_i, c_t)\big) \cdot w_H(c_t) \\
&= P_m(a_i, c_t) \cdot w_L + \big(1 - P_m(a_i, c_t)\big) \cdot (w_L + k \cdot c_t) \\
&= w_L + k \cdot c_t \cdot \big(1 - P_m(a_i, c_t)\big)
\end{aligned} \tag{3}$$

Our main result describes how optimal task complexity varies with cognitive ability.

Proposition 1 (Optimal Complexity). *As the decision-maker's cognitive ability increases, the optimal level of task complexity weakly increases.*

Proof. See Appendix A.1.1. □

The intuition is as follows. Higher cognitive ability lowers the mistake probability at every level of complexity. Because the success premium (difference between success and failure payments) is larger for more complex tasks, the gain in expected payoff from a lower mistake probability is larger on more complex tasks, making them relatively more attractive as cognitive ability rises. Under Assumption A-3 ($\beta_3 \leq 0$), higher cognitive ability also weakly slows the rate at which the mistake probability rises with complexity, reinforcing this effect. A more cognitively able decision-maker therefore chooses a weakly higher level of task complexity. The result continues to hold as long as β_3 is not sufficiently positive.

Equivalently, in terms of the success probability $(1-P_m)$, the decision-maker's problem is analogous to a monopolist's choice of a price on a linear demand curve, with complexity playing the role of price and the success probability playing the role of demand. The comparative static mirrors the standard result that an upward shift in linear demand raises the optimal price, as long as the demand curve does not steepen too much as it shifts up.

In our experiment, subjects make a binary choice between a less complex task and a more complex task. Although Proposition 1 is stated for the continuous case, its logic extends naturally to the binary case:

Proposition 2 (Binary Choice of Task Complexity)**.** *When the decision-maker faces a binary choice of task complexity, her optimal choice can switch only from the less complex task to the more complex task as her cognitive ability increases.*

Proof. See Appendix A.1.2. □

Our setup also carries a welfare implication: under optimal choice of complexity, expected payoff $\pi^*(a_i) \equiv \max_{c_t \in [0,1]} \pi(a_i, c_t)$ strictly increases in cognitive ability. A decision-maker with higher cognitive ability can choose the same complexity as a less able decision-maker. The replicated choice yields strictly higher expected payoff by A-2 (since optimal complexity is always strictly positive from the proof of Proposition 1), and re-optimizing can only raise expected payoff further. We summarize this implication:

Proposition 3 (Expected Payoff)**.** *When the decision-maker chooses task complexity optimally, her expected payoff strictly increases in cognitive ability.*

III Experimental Design

III.A Procedures

We collected experimental data from 307 student subjects at an established experimental economics laboratory at an R1 university in the United States in November 2025 with IRB approval. The experiment is pre-registered on the Open Science Framework.[7] We drew subjects from the university's student subject pool (administered using ORSEE; Greiner, 2015). The sample is balanced by gender, with 50.5% female. The experiment was programmed in oTree (Chen et al., 2016). At the beginning of the experiment,

[7]We pre-registered our plan to run sessions until we reached 300 subjects. We also collected experimental data from 103 subjects across three pilot sessions before we submitted our pre-registration. In these pilot sessions, subjects did not choose task complexity (see Appendix A.3 for details).

subjects electronically provided consent to participate. We provided the instructions to each subject on her computer screen.

We ran 11 sessions, each lasting approximately 30 minutes. Procedures were identical across sessions, although session sizes varied due to fluctuations in the show-up rate. Subjects earned \$18.62 on average, including the \$5.00 show-up fee, with total payments ranging from \$7.50 to \$30.50.

Each session consisted of three parts. In Part 1, subjects completed a test of cognitive ability followed by a belief elicitation task about their cognitive ability. Part 2 consisted of two rounds. In each round, subjects saw a pair of rule implementation tasks that differed in their levels of complexity. Subjects first chose one task from the pair, and then worked on the task they had chosen. In Part 3, subjects completed a brief demographic questionnaire that asked about gender and age.

III.B Pairs of Tasks with Choice of Complexity

We use rule implementation tasks from Oprea (2020). In each task, the subject follows a rule, formally described as a finite automaton with a particular number of states and transitions. Figures 1 and 2 provide an example rule implementation task and feedback screen. Appendix B provides a full set of screenshots from the experiment. Specifically, each task consists of 20 ticks. In each tick, the subject first types a letter and then observes a letter randomly chosen by the computer. The subject is given a rule that specifies which letter to type in the first tick and which letter to type in response to each randomly chosen letter. The rule is displayed on the screen throughout the task. Each task has a time constraint of 60 seconds.[8] We define task success as correctly typing the sequence of 20 letters within the 60-second time constraint, and task failure (which corresponds to a mistake in the model) as any outcome that does not meet this criterion. The subject receives the success payment if and only if she correctly types all 20 letters within the time constraint, and otherwise receives the failure payment. At the end of each task, the subject observes the correct sequence alongside her own responses. This feedback screen includes the subject's payment for the round and is displayed until the

[8]Oprea (2020) does not impose a time constraint. We chose 60 seconds to generate the variation in mistake rates that our analysis relies on.

subject chooses to continue, with no time constraint.[9]

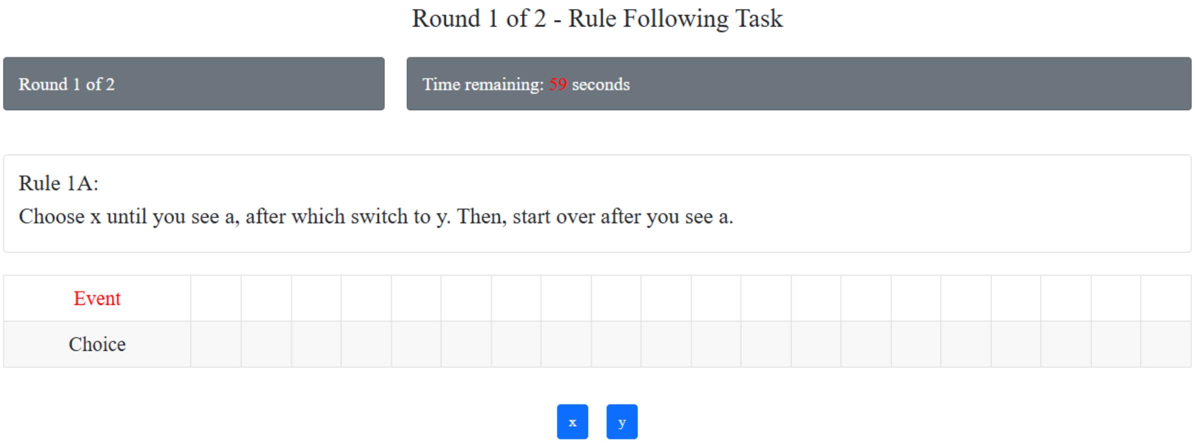


Figure 1: Experiment Interface Screenshot - Rule Implementation Task

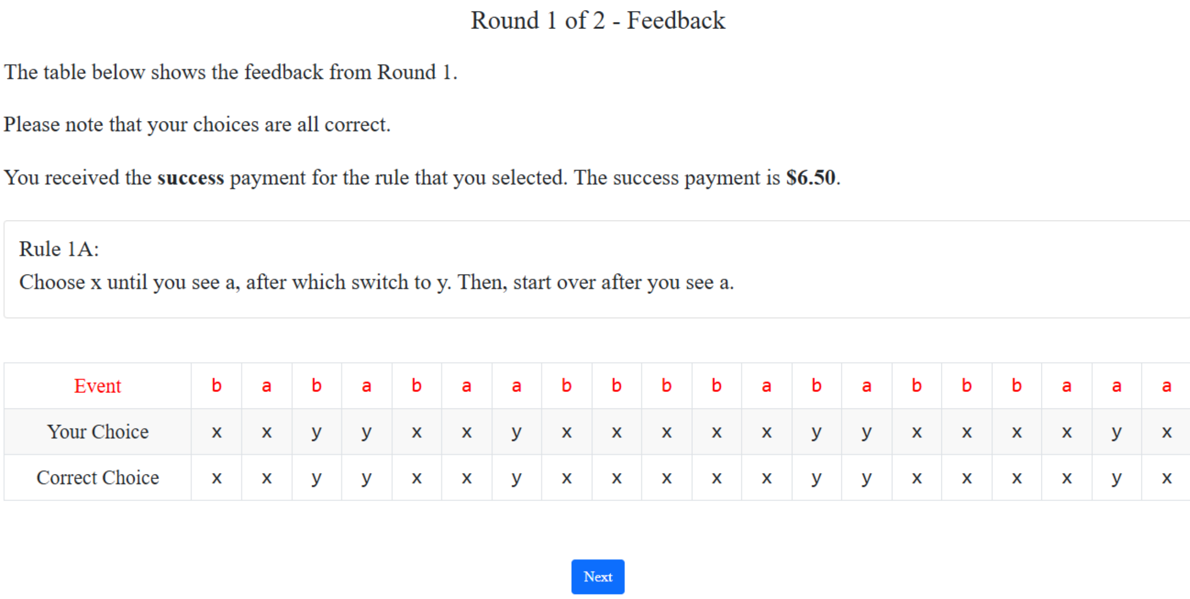


Figure 2: Experiment Interface Screenshot - Feedback Screen

[9] A possible concern with using rule implementation tasks is that mistakes are driven mainly by differences in effort rather than cognitive ability. However, Oprea (2020, Appendix B.3) argues against an important role for effort, noting that: failures in high-mistake rules often happen far into the task, and time spent on failed tasks is longer than on successful ones. Furthermore, the per-task incentives in our experiment are substantially higher than in Oprea (2020).

We select four tasks from Oprea (2020) that span a range of complexity levels and organize them into two pairs, each containing a less complex task and a more complex task. Pair 1 consists of 2S-1Ta (less complex) and 3S-3T (more complex). Pair 2 consists of 2S-2T (less complex) and Sequenceable (more complex).[10] Tasks are labeled A or B in the interface: within each pair, the task labeled B is always more complex than the one labeled A. Across the two pairs, 2S-1Ta is less complex than 2S-2T, and 3S-3T is less complex than Sequenceable. Therefore, Pair 1 is less complex overall than Pair 2. The ordering of complexity is confirmed by the mistake rates in Oprea (2020), and by the mistake rates in our pilot sessions (without choice of task complexity).

In each of two rounds, the subject is presented with one pair and chooses one of the two tasks to complete. The order of the two pairs across rounds is randomized at the subject level. The tasks are prefixed with the round number in the interface (e.g., 1A and 1B in Round 1); because pair order is randomized, the digit prefix indicates the round rather than the pair. Figures 3 and 4 provide an example of the choice pages in both rounds, with Pair 2 appearing first in this example.

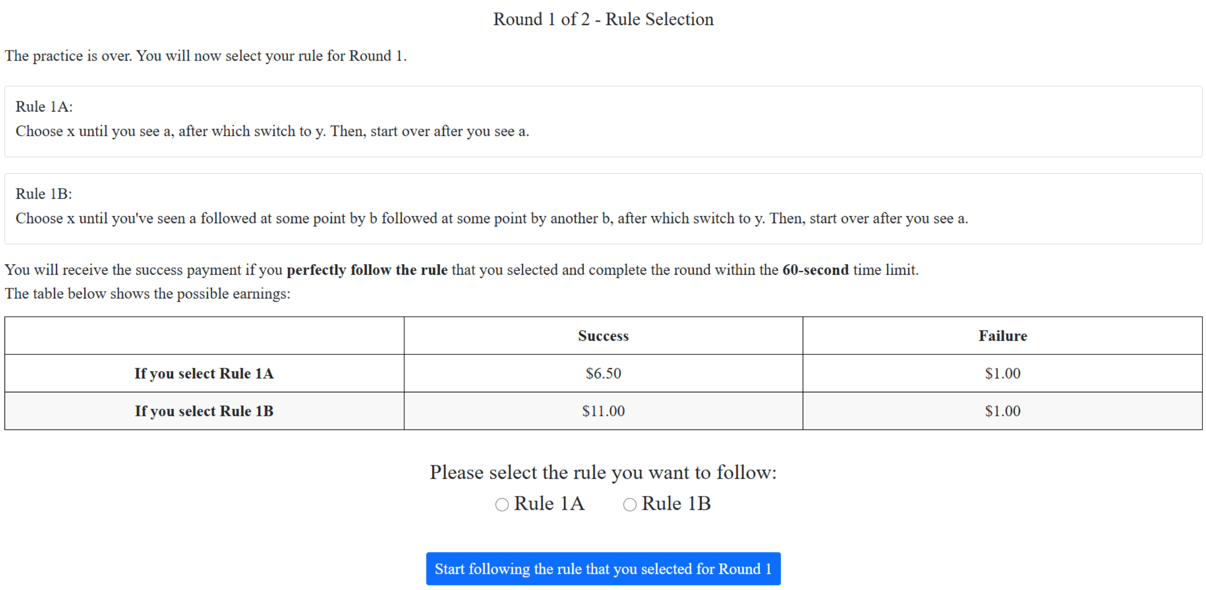


Figure 3: Experiment Interface Screenshot - Round 1 Choice Page

[10] We use the same task names as Oprea (2020). For example, 2S-1Ta refers to an automaton with two states, one transition, and one absorbing state (Sequenceable has four states and transitions). Subjects see the exact on-screen text that Oprea (2020) uses to describe each task. We preserve Oprea's original instructions, except for the additions of the choice of task and the time constraint.

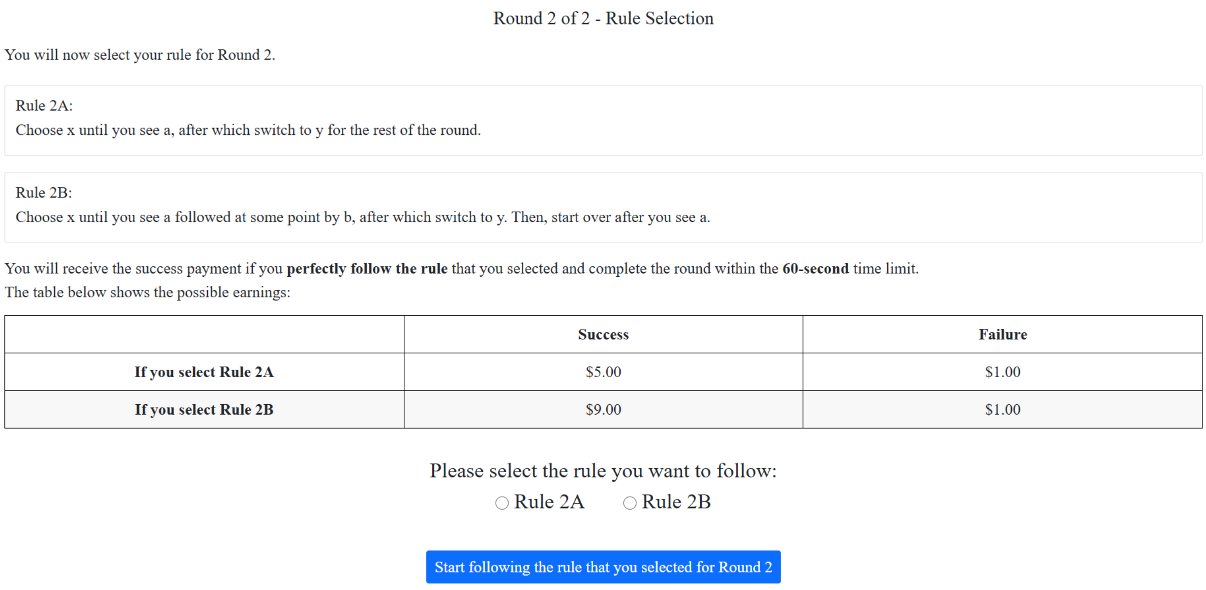


Figure 4: Experiment Interface Screenshot - Round 2 Choice Page

Table 1 summarizes the payment structure. The more complex task in each pair offers a higher success payment, creating a tradeoff between the reward from success and the probability of success. The failure payment is $1.00 for all tasks. As Pair 1 is relatively less complex than Pair 2, the success payment for each task in Pair 1 is lower than that for its counterpart in Pair 2. This payment structure reflects our model, in which the failure payment is constant, and the success payment rises with complexity.

After subjects had read the instructions and previewed the payment structure and the on-screen text descriptions of the four tasks used in Pair 1 and Pair 2, they worked on five unpaid practice tasks. The practice lets subjects learn the structure of the rule implementation tasks and helps them understand the complexity of the four tasks in Pair 1 and Pair 2. All subjects worked on the same five practice tasks without making any choice over tasks.[11]

[11]The five practice tasks are 3S-1Ta, 4S-1Ta, 3S-2T, 4S-2T, and 4S-3T, all from Oprea (2020). No practice task matches any of the four tasks in Pair 1 and Pair 2 in both the number of states and the number of transitions.

Table 1: Payment Structure

	Task	Success Payment	Failure Payment
Pair 1	2S-1Ta (less complex)	\$5.00	\$1.00
	3S-3T (more complex)	\$9.00	\$1.00
Pair 2	2S-2T (less complex)	\$6.50	\$1.00
	Sequenceable (more complex)	\$11.00	\$1.00

Notes: Task names follow Oprea (2020). We paid subjects for each pair.

III.C Measurement of Cognitive Ability and Overconfidence

To measure cognitive ability, subjects completed the 11-item matrix-reasoning test from the International Cognitive Ability Resource (Dworak et al., 2021; https://icar-project.com). This test is an open-source analogue of Raven's Progressive Matrices (Raven, 2000), and has been used in economics by, e.g., Gill and Rosokha (2024) and Gill et al. (2025). The test requires subjects to identify missing elements that complete visual patterns: Appendix B (page 3) provides a sample item. Matrix reasoning captures fluid intelligence (i.e., logical or analytical intelligence), and is a leading measure of cognitive ability that correlates strongly with general intelligence g (Gray and Thompson, 2004, Box 1) and with performance on other complex cognitive tasks (Carpenter et al., 1990). Subjects earned \$0.30 for each correct answer and had a 10-minute time limit to complete all 11 items. Since our matrix-reasoning test is an open-source analogue of Raven's Matrices, we refer to the number of correct answers in the matrix-reasoning test as the subject's Raven score, which can range from 0 to 11. In the regressions reported in Section V, we normalize the Raven score to $[0, 1]$.

After completing the test, subjects reported their belief about the number of items they solved correctly. Subjects received a \$0.20 fixed payment and earned an additional \$2.00 if their reported belief matched their Raven score exactly. We define overconfidence as the difference between a subject's reported belief and her Raven score, as pre-registered. A positive value indicates that the subject overestimates her cognitive ability, while a negative value indicates underconfidence. Subjects were informed only at the end of the experiment about whether their belief matched their Raven score.

IV Development of Hypotheses

We draw on the theoretical analysis from Section II to develop three hypotheses. All three hypotheses were pre-registered before the data were collected.

Our first hypothesis follows from Propositions 1 and 2. The model predicts that the optimal complexity level increases with cognitive ability. More cognitively able subjects succeed more often at any given task, and so they face a more favorable tradeoff between the higher success payment from a more complex task and its lower probability of success.

Hypothesis 1. *Subjects with higher cognitive ability are more likely to choose more complex tasks.*

Our second hypothesis concerns the role of overconfidence. Recall from Section III.C that we define overconfidence as the difference between a subject's belief about her Raven score and her actual Raven score, with a negative value indicating underconfidence. To allow overconfidence to affect choice, we adopt the behavioral assumption that a subject's belief about her own cognitive ability helps to shape her choice of task complexity. Under this assumption, our second hypothesis is that, conditional on cognitive ability, higher overconfidence raises chosen complexity.

Hypothesis 2. *Conditional on cognitive ability, subjects with higher overconfidence are more likely to choose more complex tasks.*

Our third hypothesis concerns the efficiency of task choice. In our model, a decision-maker chooses the task complexity that maximizes her expected payoff, so the model itself predicts no variation in optimality. We augment the model with the behavioral assumption that identifying the optimal level of task complexity is cognitively demanding. To make the optimal choice, a subject must understand the tradeoff between the success payment and the probability of success, and we further assume that higher cognitive ability is associated with a greater probability of correctly evaluating this tradeoff. Under these assumptions, the optimality of the choice improves with cognitive ability, so we expect more cognitively able subjects to choose their optimal task more frequently.

Hypothesis 3. *Subjects with higher cognitive ability are more likely to choose task complexity optimally.*

V Testing of Hypotheses

We report descriptive statistics and regression results that test the three hypotheses developed in Section IV. Section V.A describes the distributions of cognitive ability and overconfidence. Section V.B tests Hypotheses 1 and 2, and Section V.C tests Hypothesis 3.

V.A Descriptive Statistics

We begin by describing the distributions of cognitive ability and overconfidence. Figure 5 shows the distribution of Raven scores. The average Raven score is 8.0 out of a maximum of 11, with observed scores ranging from 1 to 11. The distribution is concentrated at high scores, and most subjects score between 5 and 11.

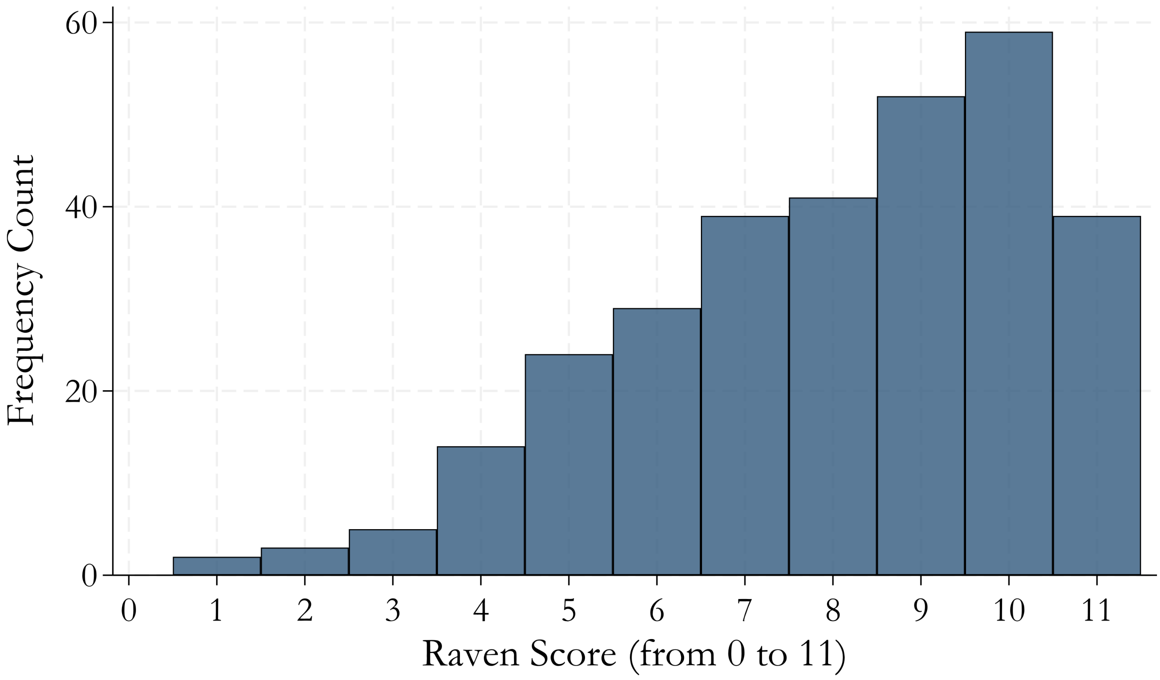


Figure 5: Distribution of Raven Score

Figure 6 shows the distribution of overconfidence, measured as the difference between a subject's belief and her actual Raven score. The distribution is roughly symmetric around zero, and most subjects have overconfidence values between -2 and $+2$. One subject reports an overconfidence value of $+9$, well above the rest of the distribution.

The main results are unaffected when we remove this outlier.[12]

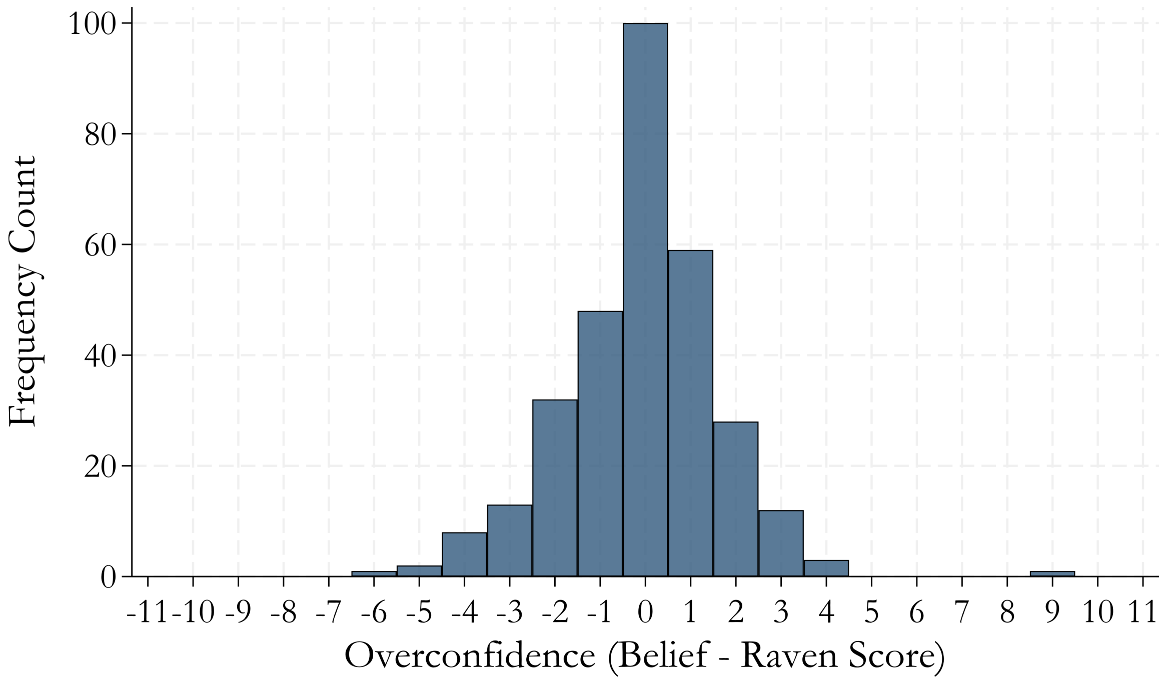
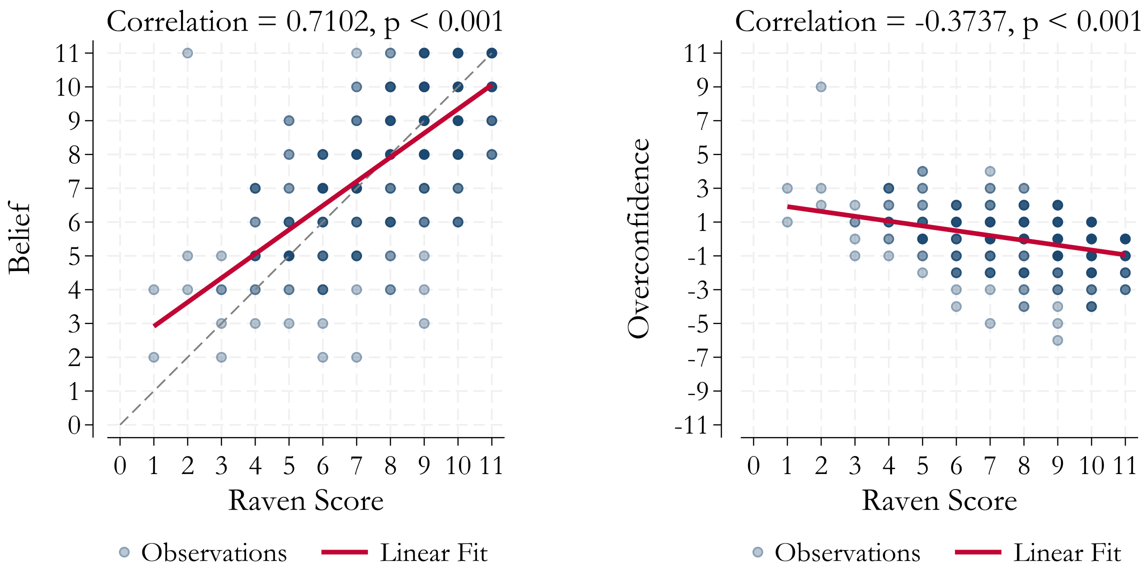


Figure 6: Distribution of Overconfidence



(a) Raven Score and Belief (b) Raven Score and Overconfidence

Figure 7: Correlation Between Raven Score, Belief, and Overconfidence

Figure 7(a) shows the correlation between subjects' Raven scores and their beliefs. The correlation between the two is 0.71 ($p < 0.001$). Subjects with low cognitive ability tend to overestimate their ability, while subjects with high cognitive ability tend to underestimate

[12]Our regression results on choice of complexity, earnings, and optimality using our choice efficiency measure are robust when we remove this outlier. The results using the coarser binary optimality measure become noisier. See Tables A.2–A.4 in Appendix A.5.

their ability. Figure 7(b) shows the correlation between Raven score and overconfidence, which is defined as the difference between a subject's belief and her score. The correlation between the two is -0.37 ($p < 0.001$).

In all regressions reported below, we normalize the Raven score to $[0, 1]$ by dividing by 11, and we normalize overconfidence to $[-1, 1]$ by dividing the difference between belief and score by 11.

V.B Choice of Task Complexity and Earnings

Table 2 reports OLS regressions of task choice on cognitive ability and overconfidence. The dependent variable is a binary indicator equal to one if the subject chose the more complex task within a pair of tasks. Columns (1)–(2) pool both pairs, columns (3)–(4) report results for Pair 1, and columns (5)–(6) report results for Pair 2.

We find strong support for Hypothesis 1: Raven score predicts the choice of the more complex task in both pairs. Subjects with higher Raven scores choose the more complex task substantially more often. An increase in the normalized Raven score from 0 to 1 is associated with a 36 percentage-point higher probability of choosing the more complex task, on average. This positive effect is robust whether we pool the data (Column 1 of Table 2) or analyze each pair separately (Columns 3 and 5 of Table 2).

Result 1. *As predicted by our model, more cognitively able subjects choose more complex tasks.*

We also find strong support for Hypothesis 2: overconfidence predicts the choice of the more complex task in both pairs. Adding overconfidence to Columns 2, 4, and 6 of Table 2, we find that, conditional on cognitive ability, more overconfident subjects (or less underconfident subjects) choose the more complex task substantially more often. As shown in Figure 6, most subjects (87%) have raw overconfidence scores in the range $[-2, 2]$. An increase in overconfidence over this range is associated with a 21 percentage-point higher probability of choosing the more complex task, on average ($0.584 \times \frac{4}{11} \approx 0.212$).[13]

Result 2. *Controlling for cognitive ability, more overconfident subjects choose more complex tasks.*

[13] Controlling for overconfidence also raises the coefficient on Raven score in all specifications. This follows mechanically from the positive correlation between overconfidence and choice of the more complex task, together with the negative correlation between Raven score and overconfidence.

Table 2: Effect of Cognitive Ability and Overconfidence on Complexity Choice

DV: Choose More Complex Task	Pooled		Pair 1		Pair 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Raven Score $[0, 1]$	0.363***	0.551***	0.297**	0.494***	0.428***	0.609***
	(0.125)	(0.132)	(0.147)	(0.160)	(0.143)	(0.149)
Overconfidence $[-1, 1]$		0.584***		0.608***		0.559***
		(0.171)		(0.186)		(0.187)
Observations	614	614	307	307	307	307
Mean of DV	0.511	0.511	0.531	0.531	0.492	0.492

Notes: OLS regressions. The dependent variable is a binary indicator equal to one if the subject chose the more complex task within a pair of tasks. Raven score is normalized to $[0, 1]$. Overconfidence is defined as the difference between belief and Raven score, normalized to $[-1, 1]$. All specifications include categorical controls for gender, age, and the order of the two pairs. Columns (1)–(2) additionally include a pair fixed effect. Heteroskedasticity-robust standard errors clustered at the subject level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-sided tests).

Our model also predicts that earnings rise with cognitive ability (Proposition 3). Table 3 reports OLS regressions of earnings on cognitive ability and overconfidence. The dependent variable is the subject's realized earnings, in dollars. We find that Raven score predicts earnings in both pairs. Controlling for cognitive ability, overconfidence predicts earnings in Pair 2, but not in Pair 1: our model does not make a prediction about the effect of overconfidence on earnings, and we discuss this result in Section V.C.

Table 3: Effect of Cognitive Ability and Overconfidence on Earnings

DV: Earnings	Pooled		Pair 1		Pair 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Raven Score $[0, 1]$	2.894***	3.573***	2.581***	2.537***	3.206***	4.609***
	(0.796)	(0.893)	(0.842)	(0.928)	(1.133)	(1.261)
Overconfidence $[-1, 1]$		2.101*		-0.136		4.338**
		(1.210)		(1.082)		(1.700)
Observations	614	614	307	307	307	307
Mean of DV	5.184	5.184	5.130	5.130	5.238	5.238

Notes: OLS regressions. The dependent variable is the subject's realized earnings in dollars (success or failure payment for the task chosen from a pair of tasks). Raven score is normalized to $[0, 1]$. Overconfidence is defined as the difference between belief and Raven score, normalized to $[-1, 1]$. All specifications include categorical controls for gender, age, and the order of the two pairs. Columns (1)–(2) additionally include a pair fixed effect. Heteroskedasticity-robust standard errors clustered at the subject level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-sided tests).

V.C Optimality of Task Choice

We now turn to Hypothesis 3. To compute each subject's optimal choice in a pair of tasks that vary in complexity, we need to estimate her probability of success on each of the two tasks. We cannot simply regress observed task success on observed individual characteristics because each subject's success or failure is observed only on the task she chose, and unobserved individual characteristics can shift both task choice and task success. For example, suppose an unobserved trait, such as task-specific skill, raises both the probability that a subject chooses the more complex task and her probability of succeeding at it. Subjects who choose the more complex task then have higher unobserved task-specific skill on average. A naive regression of observed success on observed characteristics among subjects who chose the more complex task therefore overestimates the success probability that an average subject would have on the more complex task.

To account for endogenous selection, we estimate a four-equation random-effects probit model that leverages the panel structure of our experiment. Appendix A.2 provides the full details of the model and estimation. We observe each subject choosing a task in each of two pairs, and we observe her outcome in the chosen task. The model jointly estimates the choice equation for each pair and the success equation for each task in Pair 2, with a subject-level random effect that enters all four equations and captures unobserved individual traits that can shift both task choice and task success. We find that the random effect is jointly significant in the choice equations ($p < 0.001$), so unobserved traits have an effect on task choice.[14]

Observed success rates for the less complex task in Pair 1 are close to 100%, so we have insufficient variation to identify a Pair 1 success equation for that task. We therefore restrict our optimality analysis to Pair 2. Using the estimated success equations for Pair 2 and the estimated random effect for each subject, we are able to derive estimated success probabilities for each subject on each task in Pair 2. Subsequently, we compute the expected payoff of each task in Pair 2 for each subject and define two measures of choice optimality. *Efficiency* is the ratio of the expected payoff from the chosen task to the expected payoff from the optimal task; efficiency equals one when the subject chooses

[14] We follow, e.g., Heckman and Vytlacil (2005) in using a latent factor structure to account for endogenous selection (see also Aakvik et al., 2005, who use a random effects model to capture the latent factor). See Heckman et al. (2006) for an application to a setting with multiple discrete choices and outcomes. We estimate our random effects model by maximum likelihood with Gauss-Hermite quadrature, following, e.g., Rabe-Hesketh et al. (2005).

optimally and is less than one otherwise. *Binary optimality* is a binary indicator equal to one if the subject chose the task with the higher expected payoff. Unlike binary optimality, efficiency weights mistakes by their payoff consequences.[15] We also distinguish two types of suboptimal choice: a subject is *undercautious* if she chose the more complex task when the less complex task had a higher expected payoff, and *overcautious* if she chose the less complex task when the more complex task had a higher expected payoff.

Figure 8 shows the distribution of decision types for Pair 2. About 80% of subjects choose optimally: roughly 50% optimally choose the less complex task and 30% optimally choose the more complex task. The remaining subjects are almost all undercautious, choosing the more complex task when they should have chosen the less complex task.

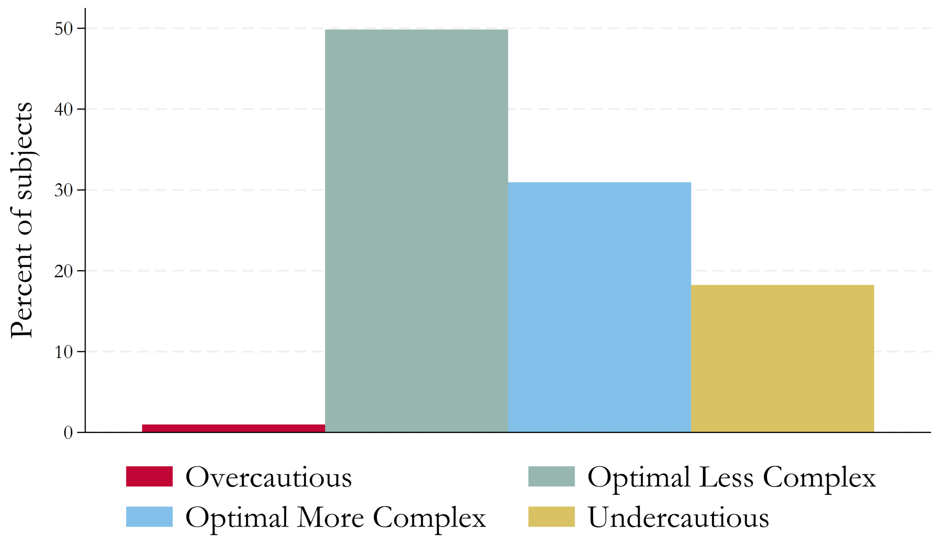


Figure 8: Decision Classification for Pair 2

Table 4 reports OLS regressions of efficiency and binary optimality on cognitive ability and overconfidence for Pair 2. We find evidence consistent with Hypothesis 3: Raven score predicts choice efficiency, a continuous measure that accounts for the payoff consequences of mistakes. Raven score also predicts binary optimality, a coarse measure that weights all mistakes equally regardless of their payoff consequences, although the effect is not statistically significant at the 5% level.

Result 3. *More cognitively able subjects make more efficient choices of task complexity.*

Recall that we have no hypothesis linking overconfidence to optimality. When we add overconfidence in columns (2) and (4) of Table 4, overconfidence has a negative effect on binary optimality, but no statistically significant effect on efficiency. The negative

[15] Appendix A.2.4 sets out the construction procedure for both optimality measures.

association between overconfidence and binary optimality is driven by undercautious overconfident subjects who choose the more complex task when the less complex task offers a higher expected payoff (we know this from Figure 8, which shows that almost all subjects who fail to choose optimally are undercautious). These mistakes are not large enough in payoff terms, however, to register as a statistically significant effect on efficiency. The positive association between overconfidence and Pair 2 earnings (Table 3) remains a puzzle, and may reflect a productive dimension of ability that is correlated with overconfidence but not captured by the Raven score.

Table 4: Effect of Cognitive Ability and Overconfidence on Optimality (Pair 2)

DV: Measurements of Optimality	Efficiency		Binary Optimality	
	(1)	(2)	(3)	(4)
Raven Score $[0, 1]$	0.153***	0.124**	0.209*	0.113
	(0.055)	(0.055)	(0.116)	(0.118)
Overconfidence $[-1, 1]$		-0.089		-0.296**
		(0.071)		(0.144)
Observations	307	307	307	307
Mean of DV	0.931	0.931	0.808	0.808

Notes: OLS regressions restricted to Pair 2. The dependent variable "efficiency" is the ratio of the expected payoff from the chosen task to the expected payoff from the optimal task. The dependent variable "binary optimality" is an indicator for choosing the task with the higher expected payoff. Expected payoffs are computed using subject-specific success probabilities estimated from the four-equation random-effects probit model (see Appendix A.2). Raven score is normalized to $[0, 1]$. Overconfidence is defined as the difference between belief and Raven score, normalized to $[-1, 1]$. All specifications include categorical controls for gender, age, and the order of the two pairs. Heteroskedasticity-robust standard errors clustered at the subject level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-sided tests).

V.D Summary of Hypothesis Testing

Taken together, our results support all three pre-registered hypotheses. Cognitive ability predicts the choice of the more complex task in both pairs (Hypothesis 1; Result 1), and overconfidence predicts the choice of the more complex task in both pairs, conditional on cognitive ability (Hypothesis 2; Result 2). Cognitive ability also predicts the efficiency of task choice (Hypothesis 3; Result 3). In addition, consistent with Proposition 3, we find that cognitive ability predicts realized task earnings in both pairs. These findings establish that cognitive ability and overconfidence are independent predictors of the choice of task complexity, and that more cognitively able subjects choose task complexity more efficiently.

VI Conclusion

Our paper makes three contributions. First, we extend the literature on choice of task complexity by linking cognitive ability and overconfidence jointly to selection between complex tasks that differ in their success–payment tradeoff. Second, we provide evidence that cognitive ability shapes the optimality of complexity choices, complementing prior work on cognition and decision quality in fixed-complexity settings. Third, we document a sharp asymmetry: when subjects err, they overreach by choosing tasks that are too complex, with direct implications for how organizations should design feedback over self-selected task menus.

These findings suggest that self-selected task menus can work well, but that organizations should design task menus, incentives for choosing more complex tasks, and feedback structures together. A menu that lets workers choose task complexity can allocate able workers to demanding tasks, and rewards for completing more complex tasks can make those choices attractive. At the same time, workers may misjudge their own ability or their probability of success on more complex tasks. When rewards rise mechanically with task complexity, overambitious workers may therefore choose tasks for which the expected payoff is lower. Organizations can preserve the benefits of self-selection by pairing complex-task choices with clear information and feedback, such as historical success rates for comparable tasks, low-stakes trial assignments before full responsibility, decision aids that make the payoff tradeoff salient, and post-project reviews that distinguish poor task choice from poor task execution.

Our analysis suggests directions for future work. One direction is strategic interaction. In many workplaces, the complexity of tasks chosen by coworkers, competitors, or team members directly affects a worker's own payoffs. Embedding choices of task complexity in cooperative or competitive environments could therefore connect our results to team assignment, promotion systems, and organizational incentive design. A second direction concerns dynamic settings with learning and skill accumulation. People often face repeated decisions about task complexity, observe feedback, and invest in skills, so it would be valuable to understand when feedback corrects overreach and when it instead reinforces miscalibrated confidence.

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Appendix A:
Supplemental Appendix

(Intended for Online Publication)

Appendix A.1 Additional Theoretical Analysis

Appendix A.1.1 Proof of Proposition 1

Proof. First, we record the parameter sign restrictions on α, β_1, β_2, and β_3 implied by **A-1** through **A-4**. We use these restrictions throughout the proof.

Assumption **A-2** requires $\beta_1 + \beta_3 c_t < 0$ for all $c_t \in [0, 1]$. Evaluating at $c_t = 0$ yields the necessary sign condition

$$\beta_1 < 0.$$

Assumption **A-1** requires $\beta_2 + \beta_3 a_i > 0$ for all $a_i \in [0, 1]$. Evaluating at $a_i = 0$ yields the necessary sign condition

$$\beta_2 > 0.$$

Because $P_m(a_i, c_t)$ is bilinear and, by **A-1** and **A-2**, strictly increasing in c_t for every $a_i \in [0, 1]$ and strictly decreasing in a_i for every $c_t \in [0, 1]$, the maximum of P_m over $[0, 1]^2$ is attained at $(a_i, c_t) = (0, 1)$ and the minimum at $(a_i, c_t) = (1, 0)$. Assumption **A-4** thus reduces to two conditions: $P_m(0, 1) = \alpha + \beta_2 \leq 1$ and $P_m(1, 0) = \alpha + \beta_1 \geq 0$.

Combining $\alpha + \beta_1 \geq 0$ with $\beta_1 < 0$ gives $\alpha \geq -\beta_1 > 0$. Combining $\alpha + \beta_2 \leq 1$ with $\beta_2 > 0$ gives $\alpha \leq 1 - \beta_2 < 1$. Hence, the necessary condition

$$\alpha \in (0, 1).$$

Finally, assumption **A-3** states directly that

$$\beta_3 \leq 0.$$

To find the unconstrained optimal complexity level, we derive the first-order and second-order conditions for expected payoff with respect to c_t. Differentiating Equation

(3), we get:

$$\begin{aligned}\frac{\partial \pi}{\partial c_t} &= k\Big[1 - P_m(a_i, c_t) - c_t \frac{\partial P_m(a_i, c_t)}{\partial c_t}\Big] \\ &= k\Big[1 - \big(\alpha + \beta_1 a_i + \beta_2 c_t + \beta_3 a_i c_t\big) - c_t\big(\beta_2 + \beta_3 a_i\big)\Big] \\ &= k\Big[1 - \alpha - \beta_1 a_i - 2\beta_2 c_t - 2\beta_3 a_i c_t\Big] \qquad (4)\end{aligned}$$

$$\frac{\partial^2 \pi}{\partial c_t^2} = -2k\big(\beta_2 + \beta_3 a_i\big) \ < 0 \text{ by } \textbf{A-1}$$

To determine the unconstrained optimal complexity level c^u, we set the first-order condition to zero. This yields the following solution for c^u:

$$c^u = \frac{1 - \alpha - \beta_1 a_i}{2\big(\beta_2 + \beta_3 a_i\big)} \qquad (5)$$

By **A-1**, $\beta_2 + \beta_3 a_i > 0$; and since $\alpha < 1$ and $\beta_1 a_i \leq 0$ (from $\beta_1 < 0$ by **A-2** and $a_i \geq 0$), $1 - \alpha - \beta_1 a_i > 0$. Hence $c^u > 0$. By concavity, the global optimal solution c^* is

$$c^* = \min\Big\{c^u, 1\Big\} \qquad (6)$$

To investigate how the unconstrained optimal complexity level c^u is affected by cognitive ability, we differentiate c^u with respect to a_i:

$$\frac{dc^u}{da_i} = \frac{-\beta_1(2\beta_2 + 2\beta_3 a_i) - (1 - \alpha - \beta_1 a_i)(2\beta_3)}{(2\beta_2 + 2\beta_3 a_i)^2} = \frac{M}{(2\beta_2 + 2\beta_3 a_i)^2} \qquad (7)$$

where $M \equiv -2\beta_1\beta_2 - 2\beta_3(1 - \alpha)$. The denominator is strictly positive by **A-1**, so $dc^u/da_i > 0$ if and only if $M > 0$. Because $\beta_1 < 0$, $\beta_2 > 0$, $\alpha \in (0, 1)$, and $\beta_3 \leq 0$, M is strictly positive.

Therefore, c^u strictly increases in a_i. Whenever $c^u(a_i) < 1$, c^* tracks c^u and strictly increases with a_i; once $c^u(a_i) \geq 1$, the constraint binds and $c^* = 1$.

The proof uses **A-3** in one place only, to show that $M > 0$. Therefore, **A-3** is a sufficient condition for Proposition 1, and Proposition 1 continues to hold as long as $\beta_3 < -\beta_1\beta_2/(1 - \alpha)$, so that M remains strictly positive.

□

Appendix A.1.2 Proof of Proposition 2

Proof. Let c_L and c_H denote the complexity levels of the less complex and more complex tasks in the binary choice, with $0 \leq c_L < c_H \leq 1$. Define the expected-payoff difference between the more complex task and the less complex task as

$$\Delta(a_i) \equiv \pi(a_i, c_H) - \pi(a_i, c_L).$$

Using Equation (3), we get

$$\begin{aligned}\Delta(a_i) &= kc_H\big(1 - P_m(a_i, c_H)\big) - kc_L\big(1 - P_m(a_i, c_L)\big) \\ &= kc_H\Big[1 - \alpha - \beta_1 a_i - \beta_2 c_H - \beta_3 a_i c_H\Big] - kc_L\Big[1 - \alpha - \beta_1 a_i - \beta_2 c_L - \beta_3 a_i c_L\Big] \\ &= k\Big[(c_H - c_L)(1 - \alpha - \beta_1 a_i) - (\beta_2 + \beta_3 a_i)(c_H^2 - c_L^2)\Big] \\ &= k(c_H - c_L)\Big[1 - \alpha - \beta_2(c_H + c_L) - a_i\big(\beta_1 + \beta_3(c_H + c_L)\big)\Big].\end{aligned} \tag{8}$$

Differentiating with respect to cognitive ability gives

$$\frac{d\Delta(a_i)}{da_i} = -k(c_H - c_L)\big(\beta_1 + \beta_3(c_H + c_L)\big). \tag{9}$$

By **A-2**, we have $\beta_1 < 0$ (see proof of Proposition 1). By **A-3**, we have $\beta_3 \leq 0$. Since $c_H + c_L > 0$, it follows that

$$\beta_1 + \beta_3(c_H + c_L) < 0. \tag{10}$$

Because $k > 0$ and $c_H - c_L > 0$, we therefore have

$$\frac{d\Delta(a_i)}{da_i} > 0.$$

Hence, the expected-payoff difference between the more complex task and the less complex task is strictly increasing in cognitive ability, giving the result.

Note that **A-3** is a sufficient condition for Proposition 2, which continues to hold as long as $\beta_3 < -\frac{\beta_1}{c_H + c_L}$, so that Equation (10) continues to hold.

□

Appendix A.2 Random-Effects Probit Model and Estimation

This appendix details the four-equation random-effects probit model introduced in Section V.C. We use the estimated model to compute subject-specific success probabilities on each task in Pair 2, which we then use to construct the optimality measures used in Section V.C.

Appendix A.2.1 Specification

For subject i and pair of tasks $p \in \{1, 2\}$, let $\text{choice}_{ip} \in \{0, 1\}$ indicate the choice of the less complex or more complex task. For Pair 2, let $\text{success}^1_{i2} \in \{0, 1\}$ denote the success indicator if subject i chose the more complex task (observed only when $\text{choice}_{i2} = 1$), and let $\text{success}^0_{i2} \in \{0, 1\}$ denote the corresponding success indicator if she chose the less complex task (observed only when $\text{choice}_{i2} = 0$).

Let X_i collect the subject's time-invariant covariates: the Raven score, overconfidence, gender, and age. Let $Z_{ip} \in \{0, 1\}$ be an indicator equal to one if the random order assigned pair p first to subject i. Let η_i denote a subject-level latent factor capturing unobserved heterogeneity that can affect both the choice of task and success conditional on task choice. We assume $\eta_i \sim \mathcal{N}(0, 1)$ (with unit variance normalized for identification) and independent of X_i and Z_{ip}.

The random-effects model consists of four probit equations estimated jointly, with freely estimated factor loadings λ on η_i (the superscript S denotes parameters of the selection (choice) equations):

$$\text{choice}_{i1} = 1 \iff X_i'\gamma_1^S + Z_{i1}\delta_1^S + \lambda_1^S\eta_i + \varepsilon_{i1}^S > 0, \tag{11}$$

$$\text{choice}_{i2} = 1 \iff X_i'\gamma_2^S + Z_{i2}\delta_2^S + \lambda_2^S\eta_i + \varepsilon_{i2}^S > 0, \tag{12}$$

$$\text{success}^1_{i2} = 1 \iff X_i'\gamma_2^1 + Z_{i2}\delta_2^1 + \lambda_2^1\eta_i + \varepsilon_{i2}^1 > 0, \tag{13}$$

$$\text{success}^0_{i2} = 1 \iff X_i'\gamma_2^0 + Z_{i2}\delta_2^0 + \lambda_2^0\eta_i + \varepsilon_{i2}^0 > 0, \tag{14}$$

where the idiosyncratic shocks ε are standard normal, mutually independent, and independent of η_i and X_i.

Appendix A.2.2 Estimation

Table A.1 reports the estimated coefficients of the four-equation probit model. The first two columns describe the choice of the more complex task in Pair 1 and Pair 2. The last two columns describe task success in Pair 2, conditional on the chosen task.

Table A.1: Random-Effects Probit Estimates

DV	Choose More Complex Task		Success in Pair 2	
	Pair 1	Pair 2	More Complex Task	Less Complex Task
Raven score $[0, 1]$	2.496	3.284	3.367	1.355
	(1.751)	(2.542)	(3.427)	(0.929)
Overconfidence $[-1, 1]$	3.137	3.114	1.905	2.816***
	(2.330)	(2.148)	(3.064)	(1.071)
Loading on η_i	1.697	1.798	1.630	0.636
	(1.431)	(1.662)	(2.123)	(0.505)
Observations	307	307	151	156
Mean of DV	0.531	0.492	0.563	0.526

Notes: We estimate the four-equation random-effects probit model using maximum likelihood (specifically using the gsem command in Stata with 20-point Gauss-Hermite quadrature for numerical integration). All specifications include categorical controls for gender, age, and the order of the two pairs. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels (two-sided tests).

We assess whether the latent factor η_i matters for task choice by testing a joint restriction on the factor loadings:

$$H_0 : \lambda_1^S = \lambda_2^S = 0.$$

The Wald test rejects H_0 ($p < 0.001$), so the unobserved trait has an effect on task choice beyond the observed covariates.

Appendix A.2.3 Predicted Success Probabilities

For each subject, we first compute the predicted random effect $\hat{\eta}_i$ as the empirical Bayes posterior mean of η_i given the subject's observed data and the estimated model parameters (obtained in Stata via predict after gsem). Using $\hat{\eta}_i$ and the estimated coefficients, we then compute predicted success probabilities for each Pair 2 task as:

$$\begin{aligned} \widehat{\Pr}(\text{success}_{i2}^1 = 1) &= \Phi\Big(X_i'\hat{\gamma}_2^1 + Z_{i2}\hat{\delta}_2^1 + \hat{\lambda}_2^1\hat{\eta}_i\Big) \\ \widehat{\Pr}(\text{success}_{i2}^0 = 1) &= \Phi\Big(X_i'\hat{\gamma}_2^0 + Z_{i2}\hat{\delta}_2^0 + \hat{\lambda}_2^0\hat{\eta}_i\Big) \end{aligned} \tag{15}$$

where Φ is the standard normal CDF.

Appendix A.2.4 Optimality Measures

As described in Table 1, the success payment of the more complex task in Pair 2 is \$11.00 and the success payment of the less complex task in Pair 2 is \$6.50. The failure payment of both tasks in Pair 2 is \$1.00. Let $\widehat{\mathbb{E}}[\pi^1_{i2}]$ denote the expected payoff of the more complex task in Pair 2 for subject i and $\widehat{\mathbb{E}}[\pi^0_{i2}]$ denote the expected payoff of the less complex task in Pair 2 for subject i. Based on the predicted success probabilities, the expected payoffs are calculated as follows:

$$
\begin{aligned}
\widehat{\mathbb{E}}[\pi^1_{i2}] &= 11 \cdot \widehat{\Pr}(\text{success}^1_{i2} = 1) + 1 \cdot \big(1 - \widehat{\Pr}(\text{success}^1_{i2} = 1)\big) \\
\widehat{\mathbb{E}}[\pi^0_{i2}] &= 6.5 \cdot \widehat{\Pr}(\text{success}^0_{i2} = 1) + 1 \cdot \big(1 - \widehat{\Pr}(\text{success}^0_{i2} = 1)\big)
\end{aligned} \tag{16}
$$

The optimal task for subject i is the one with the higher predicted expected payoff. In our data, there are no ties: each subject has a unique optimal choice. The subject's choice is *optimal* if her chosen task matches the optimal task, *undercautious* if she chose the more complex task when the less complex task was optimal, and *overcautious* if she chose the less complex task when the more complex task was optimal. Efficiency is defined as

$$
\text{efficiency}_{i2} = \frac{\widehat{\mathbb{E}}[\pi^{\text{chosen}}_{i2}]}{\max\left\{\widehat{\mathbb{E}}[\pi^1_{i2}], \widehat{\mathbb{E}}[\pi^0_{i2}]\right\}},
$$

where "chosen" refers to the task that subject i actually chose. Efficiency equals one when the subject chooses optimally and less than one otherwise. These are the decision-classification and efficiency measures reported in Section V.C and Figure 8.

Appendix A.3 Pilot Sessions

The pilot collected data from 103 student subjects across three sessions in April 2025.

Each session consisted of three parts. In Part 1, subjects completed a battery of cognitive ability measures that included the 11-item matrix-reasoning test from the International Cognitive Ability Resource (Dworak et al., 2021).[16] Subjects earned \$0.30 for each correct answer. In Part 2, subjects worked on all 14 rule implementation tasks from Oprea (2020), with each task completed twice in randomized order, and subjects earned \$0.70 for each task that they correctly completed. In Part 3, subjects answered a brief demographic questionnaire.

Two features of the pilot deserve explicit emphasis. First, subjects did not choose tasks in the pilot, so task assignment was exogenous. This contrasts with the main experiment, in which subjects choose between a less complex and a more complex task within each pair. Second, the visual presentation and time constraints of the matrix-reasoning test and the rule implementation tasks in the pilot are identical to those in the main experiment, and subjects received the same rule implementation task feedback as in the main experiment.

[16] See Section III.C for test implementation details.

Appendix A.4 Model Estimation

We use the pilot data (see Appendix A.3) to estimate the linear mistake-probability function in Equation (1) separately using each of the two task pairs from the main experiment. Pair 1 consists of 2S-1Ta (less complex) and 3S-3T (more complex). Pair 2 consists of 2S-2T (less complex) and Sequenceable (more complex). We rely on the pilot data rather than the main-experiment data because task assignment in the pilot is exogenous, which allows us to estimate the mistake-probability function without selection induced by task choice.[17]

Within each pair, we estimate the model using the lower complexity level in the pair ($c_{\min}$) and the higher complexity level in the pair ($c_{\max}$). We estimate the following OLS regression, using an indicator for the more complex task on the right-hand side:

$$P_m(a_i, c_t) = \alpha + \beta_1 a_i + \beta_2 \mathbf{1}(c_t = c_{\max}) + \beta_3 a_i \mathbf{1}(c_t = c_{\max}) \tag{17}$$

The numerical values of $c_{\min}$ and $c_{\max}$ on the $[0, 1]$ scale are not identified from our data. Due to linearity, the model is invariant under positive affine transformations (with appropriately rescaled parameters). Thus, we can use an indicator for $c_{\max}$ in Equation (17). We note that our estimates should be interpreted as applying only to the interval from $c_{\min}$ to $c_{\max}$.

We estimate our model using OLS regression without imposing any parameter constraints, and then verify the model's assumptions ex post. For each pair, all four assumptions **A-1** through **A-4** are satisfied.

[17] Subjects face each task twice in the pilot, while subjects face each task at most once in the main experiment. Therefore, to maintain consistency with the main experiment, we use subjects' first attempt at each task to estimate the model.

Appendix A.5 Further Tables

Table A.2: Effect of Cognitive Ability and Overconfidence on Complexity Choice (Excluding the Outlier)

DV: Choose More Complex Task	Pooled		Pair 1		Pair 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Raven Score $[0, 1]$	0.392***	0.551***	0.326**	0.494***	0.459***	0.609***
	(0.124)	(0.132)	(0.147)	(0.160)	(0.142)	(0.150)
Overconfidence $[-1, 1]$		0.537***		0.567***		0.507**
		(0.181)		(0.199)		(0.198)
Observations	612	612	306	306	306	306
Mean of DV	0.510	0.510	0.529	0.529	0.490	0.490

Notes: We run the same OLS regressions as in Table 2, without including the one subject with overconfidence of +9. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A.3: Effect of Cognitive Ability and Overconfidence on Earnings (Excluding the Outlier)

DV: Earnings	Pooled		Pair 1		Pair 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Raven Score $[0, 1]$	2.814***	3.574***	2.477***	2.538***	3.151***	4.610***
	(0.803)	(0.894)	(0.849)	(0.929)	(1.148)	(1.262)
Overconfidence $[-1, 1]$		2.566**		0.204		4.929***
		(1.234)		(1.130)		(1.759)
Observations	612	612	306	306	306	306
Mean of DV	5.198	5.198	5.144	5.144	5.252	5.252

Notes: We run the same OLS regressions as in Table 3, without including the one subject with overconfidence of +9. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table A.4: Effect of Cognitive Ability and Overconfidence on Optimality (Pair 2) (Excluding the Outlier)

DV: Measurements of Optimality	Efficiency		Binary Optimality	
	(1)	(2)	(3)	(4)
Raven Score $[0, 1]$	0.135**	0.124**	0.185	0.114
	(0.052)	(0.055)	(0.115)	(0.118)
Overconfidence $[-1, 1]$		-0.035		-0.240
		(0.056)		(0.148)
Observations	306	306	306	306
Mean of DV	0.933	0.933	0.810	0.810

Notes: We run the same OLS regressions as in Table 4, without including the one subject with overconfidence of +9. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Appendix B:
Experimental Screenshots

(Intended for Online Publication)

Experiment Overview

Today's experiment will last about 30 minutes.

Timeline:

- Stage 1 (11-question Test)
- Stage 2 (Economic Decisions)
- Questionnaire

Next

Stage 1 (Test)

This test is made up of 11 questions. You will have 10 minutes to complete this test.

The top right-hand corner of the screen will display the time remaining to complete the test (in seconds).

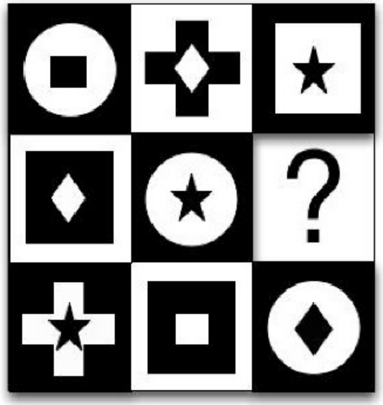
You will be paid $0.30 for each correctly answered question in this test.

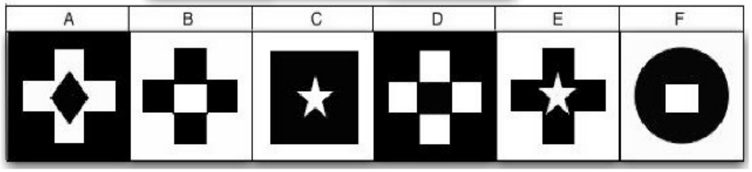
Next

Question 1 of 11

Time remaining to complete this test (seconds): 599

Please indicate which is the best answer to complete the figure below. There is only one right answer.





Select your answer and then click submit:

A B C D E F

Submit

Note: This is a sample item. See Section III.C for details.

Out of the 11 questions on the test you just completed, how many questions do you think you answered correctly?

You will earn $2 if your guess is correct.

You will also receive a fixed amount of $0.20 whether or not your guess is correct.

You will find out your earnings for this part at the end of the experiment.

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 ○ 11

Submit

Stage 2 Instructions

1. **ROUNDS, TICKS and EVENTS:**

In Stage 2 you will participate in a **rule-following task**. The Stage will be divided into 2 **ROUNDS** and each round will be divided into 20 **TICKS**. In each tick two things will happen in sequence:

- you will type a letter (which we will call your **CHOICE**)
- after you've typed your letter you will see an **EVENT** (a letter **randomly** chosen by the computer and displayed in red on your screen)

Your screen will look like the screenshot below.

2. **RULES and EARNINGS:**

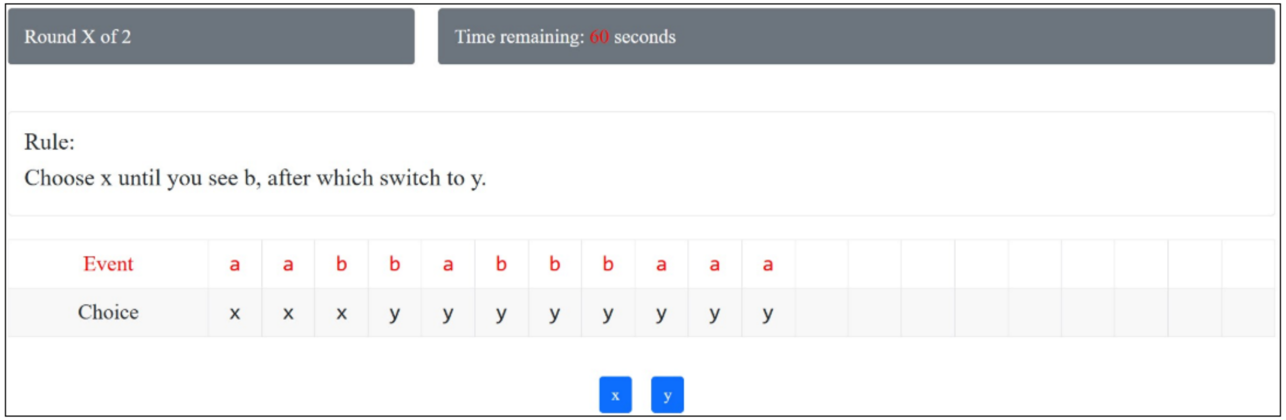
In each round we will display a **RULE** on your computer screen specifying what letter to type each tick (in the example below the rule is "Choose x until you see b, after which switch to y"). The rule will instruct you what to type in the first tick and, afterwards, what to type in response to the sequence of events you have seen so far.

2. **RULES and EARNINGS: (continued)**

If you **perfectly follow the rule** (type exactly what the rule asks for in each tick) and complete the round within the **60-second** time limit, you will **receive the success payment** for the round (otherwise you will receive the failure payment for the round).

- Example: *Suppose the rule was "Choose x for the entire round." Then you would simply type x in every tick regardless of what events have occurred.*
- Example: *Suppose instead the rule was "Choose x until after see b, after which switch to y." Now your choice depends on whether you have seen a b so far. If the events for the round were aabbabbbaaa, then you would need to type **xxxyyyyyyyy** to receive the success payment.*
- Example: *In the previous example, if the events had instead been aaaabbbbbbb you would need to type **xxxxxyyyyyy** to receive the success payment.*

Next



Stage 2 Instructions

3. **RULES and EARNINGS:**

- When a rule says to **switch** to a new letter, it is telling you to type that new letter every subsequent tick, until the rule instructs you to change again.

- When a rule says to **start over** it is telling you, for the rest of the round, to act as though all previous ticks and events had never occurred. You must therefore start by typing the first letter the rule prescribes and then follow the rule based on the events that occur after the start over (exactly as though the previous ticks and events hadn't happened).

- Example: *Suppose the rule is "Choose x until you see b, after which switch to y. Then, after you see an a start over." If the events are ababb then in order to follow the rule you must type* ***xxyxy****. Following the rule, you choose x until you see the first b (in the second tick) and then switch to y after, in the third tick. Since a occurs in the third tick, you start over in the fourth tick - from then on, you'll ignore the events in the first three ticks. The rule says to choose x until you see the first b, which occurs here in the fourth tick (remember the rule tells us to ignore anything that happened in the first three ticks), then switch to y. So in the fifth tick you switch to y.*

- When a rule says something like "if you see a **followed at some point** by c, switch to y" it is telling you that you should switch to y after you see c occur following an a, even if the c did not happen immediately after the a.

- If your rule tells you something like "choose x until you see a b, after which switch to y" and you see a b in the same tick you first chose x, then you should switch to y. That is, even if the event that triggers a switch happens immediately, you should switch right away.

4. **DETAILS:**

You will start each round with a **blank screen**, make your first choice and you will then see the event that follows in the first tick. As you make choices, you will see all of the previous ticks of the round. When all 20 ticks have occurred for the round (when you have typed 20 letters) or when time runs out, you will learn whether you made a mistake (and see the correct series of choices) and see a **button** that you must click to move onto the next round.

Back | Please click this button to continue

Round 1 of 2 - Instructions

In Round 1, you will select one of the following two rules.

Rule 1A:
Choose x until you see a, after which switch to y. Then, start over after you see a.

Rule 1B:
Choose x until you've seen a followed at some point by b followed at some point by another b, after which switch to y. Then, start over after you see a.

You will receive the success payment if you **perfectly follow the rule** that you selected and complete the round within the **60-second** time limit.
The table below shows the possible earnings:

	Success	**Failure**
If you select Rule 1A	$6.50	$1.00
If you select Rule 1B	$11.00	$1.00

Before making your choices, you will practice with five other rules. You will not be paid for this practice.
Please click the next button to continue.

Next

Round 2 of 2 - Instructions

In Round 2, you will select one of the following two rules.

Rule 2A:
Choose x until you see a, after which switch to y for the rest of the round.

Rule 2B:
Choose x until you see a followed at some point by b, after which switch to y. Then, start over after you see a.

You will receive the success payment if you **perfectly follow the rule** that you selected and complete the round within the **60-second** time limit.
The table below shows the possible earnings:

	Success	**Failure**
If you select Rule 2A	\$5.00	\$1.00
If you select Rule 2B	\$9.00	\$1.00

Before making your choices, you will practice with five other rules. You will not be paid for this practice.
Please click the next button to continue.

Next

Unpaid Practice

Please click the next button to **begin the unpaid practice**.

Next

Unpaid Practice

Practice 1 of 5

Time remaining: 59 seconds

You will not be paid for this practice.

Rule:
Choose x until you see a, after which choose x once more and then switch to y for the rest of the round.

Event																				
Choice																				

x y

Feedback from Unpaid Practice

The table below shows the feedback from the Practice 1 of 5.

Please note that your choices are all correct.

Rule:
Choose x until you see a, after which choose x once more and then switch to y for the rest of the round.

Event	a	b	a	b	b	b	b	a	b	a	a	a	a	b	a	b	b	b	a	b
Your Choice	x	x	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y
Correct Choice	x	x	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y

Next

Unpaid Practice

Practice 2 of 5

Time remaining: 59 seconds

You will not be paid for this practice.

Rule:
Choose x until you see a, after which choose y once followed by x once and then switch to y for the rest of the round.

Event																				
Choice																				

x y

Feedback from Unpaid Practice

The table below shows the feedback from the Practice 2 of 5.

Please note that your choices are all correct.

Rule:
Choose x until you see a, after which choose y once followed by x once and then switch to y for the rest of the round.

Event	b	a	b	b	b	b	b	a	a	a	a	b	b	b	a	a	a	a	a	a
Your Choice	x	x	y	x	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y
Correct Choice	x	x	y	x	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y

Next

Unpaid Practice

Practice 3 of 5

Time remaining: 59 seconds

You will not be paid for this practice.

Rule:
Choose x until you see a, after which choose x once more and then switch to y. Then, start over after you see a.

Event																				
Choice																				

x y

Feedback from Unpaid Practice

The table below shows the feedback from the Practice 3 of 5.

Please note that at least one of your choices is incorrect, or you ran out of time, or both.

Rule:
Choose x until you see a, after which choose x once more and then switch to y. Then, start over after you see a.

Event	a	a	b	a	a	b	a	a	b	a	a	a	b	b	a	a	a	b	a	b
Your Choice	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Correct Choice	x	x	y	y	x	x	y	x	x	y	x	x	y	y	y	x	x	y	y	x

Next

Unpaid Practice

Practice 4 of 5

Time remaining: 58 seconds

You will not be paid for this practice.

Rule:

Choose x until you see a, after which choose y once followed by x once and then switch to y. Then, start over after you see a.

Event																				
Choice																				

x y

Feedback from Unpaid Practice

The table below shows the feedback from the Practice 4 of 5.

Please note that at least one of your choices is incorrect, or you ran out of time, or both.

Rule:
Choose x until you see a, after which choose y once followed by x once and then switch to y. Then, start over after you see a.

Event	b	b	a	a	b	b	b	a	a	b	a	b	a	b	b	b	b	a	a	a
Your Choice	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Correct Choice	x	x	x	y	x	y	y	y	x	y	x	y	y	x	x	x	x	x	y	x

Next

Unpaid Practice

Practice 5 of 5

Time remaining: 59 seconds

You will not be paid for this practice.

Rule:

Choose x until you see a, after which switch to y. Then, after you see b, choose x once and then switch to y. Then, start over after you see a.

Event																				
Choice																				

x y

Feedback from Unpaid Practice

The table below shows the feedback from the Practice 5 of 5.

Please note that at least one of your choices is incorrect, or you ran out of time, or both.

Rule:

Choose x until you see a, after which switch to y. Then, after you see b, choose x once and then switch to y. Then, start over after you see a.

Event	a	b	a	a	a	b	a	b	b	b	a	a	b	a	b	a	a	a	b	b
Your Choice	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Correct Choice	x	y	x	y	x	y	x	y	y	y	y	x	y	x	y	y	x	y	y	x

Next

Round 1 of 2 - Rule Selection

The practice is over. You will now select your rule for Round 1.

Rule 1A:
Choose x until you see a, after which switch to y. Then, start over after you see a.

Rule 1B:
Choose x until you've seen a followed at some point by b followed at some point by another b, after which switch to y. Then, start over after you see a.

You will receive the success payment if you **perfectly follow the rule** that you selected and complete the round within the **60-second** time limit.
The table below shows the possible earnings:

	Success	**Failure**
If you select Rule 1A	\$6.50	\$1.00
If you select Rule 1B	\$11.00	\$1.00

Please select the rule you want to follow:

○ Rule 1A ○ Rule 1B

Start following the rule that you selected for Round 1

Round 1 of 2 - Rule Following Task

Round 1 of 2	Time remaining: 59 seconds

Rule 1A:
Choose x until you see a, after which switch to y. Then, start over after you see a.

Event																				
Choice																				

x y

Round 1 of 2 - Feedback

The table below shows the feedback from Round 1.

Please note that your choices are all correct.

You received the **success** payment for the rule that you selected. The success payment is **$6.50**.

Rule 1A:
Choose x until you see a, after which switch to y. Then, start over after you see a.

Event	b	a	b	a	b	a	a	b	b	b	b	a	b	a	b	b	b	a	a	a
Your Choice	x	x	y	y	x	x	y	x	x	x	x	x	y	y	x	x	x	x	y	x
Correct Choice	x	x	y	y	x	x	y	x	x	x	x	x	y	y	x	x	x	x	y	x

Next

Round 2 of 2 - Rule Selection

You will now select your rule for Round 2.

Rule 2A:
Choose x until you see a, after which switch to y for the rest of the round.

Rule 2B:
Choose x until you see a followed at some point by b, after which switch to y. Then, start over after you see a.

You will receive the success payment if you **perfectly follow the rule** that you selected and complete the round within the **60-second** time limit.
The table below shows the possible earnings:

	Success	**Failure**
If you select Rule 2A	$5.00	$1.00
If you select Rule 2B	$9.00	$1.00

Please select the rule you want to follow:

○ Rule 2A ○ Rule 2B

Start following the rule that you selected for Round 2

Round 2 of 2 - Rule Following Task

Round 2 of 2

Time remaining: 59 seconds

Rule 2A:
Choose x until you see a, after which switch to y for the rest of the round.

Event																				
Choice																				

x y

Round 2 of 2 - Feedback

The table below shows the feedback from Round 2.

Please note that at least one of your choices is incorrect, or you ran out of time, or both.

You received the **failure** payment for the rule that you selected. The failure payment is **$1.00**.

Rule 2A:
Choose x until you see a, after which switch to y for the rest of the round.

Event	b	a	a	b	a	a	b	a	a	b	b	a	a	a	b	b	a	a	b	a
Your Choice	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Correct Choice	x	x	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y	y

Next

Demographic Survey

1. What is your gender?

- ◯ Male
- ◯ Female
- ◯ Other
- ◯ Prefer Not to Say

2. What is your age?

- ◯ Below 20
- ◯ Over 20
- ◯ Prefer Not to Say

Next

Your Final Payments

In Stage 1:

- Your total earnings from the test is **$0.60**.
- Your total earnings from your guess is **$0.20**.

In Stage 2:

- Your total earnings is **$7.50**.

Your total payment, including the $5 show-up fee, is **$13.30**.

Please remain seated in your booth. The lab assistant will come to your booth to give you your cash payment.

Thank you for participating.