Correlation Neglect in College Admissions: Experimental Evidence

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Abstract

This paper explores correlation neglect in constrained Deferred Acceptance (DA) mechanisms, widely used in school choice and college admissions. Correlation neglect occurs when students overlook the correlation between admission decisions, leading to overly aggressive application strategies and increased unassignment risk. We conduct a laboratory experiment to examine the presence of correlation neglect in an education matching market and evaluate interventions designed to address this cognitive bias. We find that correlation neglect significantly influences student behavior, resulting in a higher share of aggressive rank-ordered lists. Interventions such as reminders about the correlations and personalized admission probabilities have limited impact. In contrast, switching to the Iterative DA mechanism significantly reduces the impact of correlation neglect by making contingencies more salient. Our findings suggest that dynamic mechanisms are potentially more effective than informational interventions in addressing cognitive biases in school choice, offering a promising direction for improving centralized admissions processes.

Keywords: Correlation neglect, school choice, cognitive ability, mechanism design, laboratory experiment

JEL codes: D47; D90; C92

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1 Introduction

Constrained Deferred Acceptance (DA) mechanisms are widely used in school choice and college admissions worldwide.[1] In these systems, students must carefully weigh their true preferences against the likelihood of acceptance, balancing the desire to attend top-choice schools with the need to secure a spot somewhere. The canonical framework developed by Chade and Smith (2006) studies the optimal decisions when admissions probabilities are independent. However, in practice, admissions decisions are frequently correlated due to factors such as preference homogeneity and standardized test scores. In markets with correlated admissions, students face increased risks of being rejected by multiple schools simultaneously, creating a sharp contrast in the strategy formulation of independent admissions (Ali and Shorrer, 2021).

Despite the importance of accounting for these correlations, students often fail to do so — a phenomenon known as correlation neglect. Correlation neglect is a cognitive bias where individuals overlook or underestimate the extent of correlation between events, leading to suboptimal decision making (Enke and Zimmermann, 2019). In constrained DA, this neglect of correlation can lead students to overestimate their chances of admission when applying to multiple highly competitive schools and avoid applying to safety schools (Rees-Jones et al., 2024). This oversight amplifies the risk of unassignment, as students may end up without offers if all their high-risk choices fail. This failure introduces new challenges for market designers to incorporate the effects of correlation neglect into consideration.

In this paper, we examine whether students exhibit correlation neglect in a laboratory environment designed to closely resemble real-world matching markets. We further test interventions that could help students better account for correlated admission decisions. Specifically, we focus on two sources of correlation neglect: the failure to think contingently and the complexity of the problem. If failures of contingent reasoning drive correlation neglect, increasing the salience of contingencies could help guide students toward optimal strategies. We compare the effectiveness of two interventions designed to make the contingencies more salient: providing reminders to students

[1] In Chile (Larroucau et al., 2024), China (Chen and Kesten, 2017; Wang et al., 2021), England, New York City (Haeringer and Klijn, 2009).

about the correlations and implementing an Iterative DA mechanism. Providing explicit reminders about potential correlations in the admissions process directly prompts students to consider the interdependence of their school choices. This approach aligns with existing research where reminders have been used as nudge interventions (Bettinger et al., 2012; Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019). The Iterative DA mechanism involves multiple stages of application and acceptance, allowing students to observe the outcomes of earlier stages and adjust their subsequent choices accordingly. This dynamic process naturally highlights the contingent nature of admissions. To tackle the challenge of complexity, we introduce personalized admission probabilities. We simplify the decision-making process by providing students with individualized estimates of their chances of acceptance at each school. These estimates incorporate information about the admissions correlations, helping students make more informed choices that account for this interdependence.

In our controlled school choice experiment, four students are matched with four schools using a constrained DA mechanism with two possible choices. Students' priorities are based on standardized score ranking and are public information. Students are also informed about their preferences and the distribution of others' preferences. This setup closely mimics the college admission markets in China, Turkey, and many other countries (Calsamiglia et al., 2010), where the uncertainty of admission arises from the preferences and strategies of other students. The top two ranked students have no incentive to deviate from truth-telling. Therefore, we use computers to simulate the top two students, assume they truthfully report their preferences and focus on analyzing the strategies of the third-ranked student.[2] Students repeatedly play the school choice game for 15 rounds with different preferences and payoff structures. In our design, a rational student should always prefer a school choice portfolio with reach and safety schools in all rounds.[3] In contrast, a student exhibiting correlation neglect may prefer an aggressive strategy without a safe school. The reason is that when students fail to think contingently and are rejected by their top choice, they tend to be

[2]Using computers to act as participants is not rare in school choices. See Chen et al. (2018).

[3]Following Ali and Shorrer (2021), we classify colleges as follows: A "match" is the school an applicant would choose if they could only apply to one, offering the best balance between acceptance rate and expected payoff. A "safety school" is less selective than the match, with a higher acceptance rate but a lower payoff, making it a safer but less desirable option. A "reach" is more selective than the match, with high potential rewards but a low acceptance rate, making it a less realistic primary target.

overly optimistic about their admission chances in their second-most preferred schools. This failure introduces biases when comparing the expected utilities of school portfolios with and without a safety school. We design the school choice environment in each round to introduce variations in the size of the bias driven by correlation neglect. We should observe a higher share of an aggressive strategy for a fixed group of students when the bias is larger. Therefore, the change in the ratio of aggressive school portfolios relative to the bias size in each round helps identify the existence of correlation neglect. This identification strategy is similar to those used to identify inattention in Hossain and Morgan (2006) and Chetty et al. (2009).

We find that the bias induced by correlation neglect significantly increases the share of aggressive rank-ordered lists (ROL). A one standard deviation increase in the bias leads to about 17% more mistakes, even after controlling for a rich set of characteristics, including student demographics, measures of risk aversion, ambiguity aversion and contingent thinking ability, and round and session fixed effects. An undesired consequence of correlation neglect and submitting aggressive ROL in a constrained DA mechanism is the increased risk of unassignment. We find that students are less likely to be unassigned in rounds with smaller bias, and a one standard deviation decrease in the bias results in about a 25% decrease in the ratio of unassigned students. These results suggest that a substantial fraction of students are likely to exhibit correlation neglect in school choices. One concern could be that comparisons across rounds might be invalid if students learn from the admission outcomes of previous rounds. For example, if students are unassigned in a prior round, they might adopt safer strategies in subsequent rounds. To address this concern, we plot the proportion of aggressive ROLs by round and find that this proportion does not decrease in later rounds compared to earlier ones, thereby eliminating the presence of learning effects.

Our paper further shows that providing reminders and personalized admission probabilities have a limited impact on reducing correlation neglect. The share of aggressive ROLs in each round of the reminder treatment is almost identical to those in the baseline group. Although the treatment providing personalized admission chances lowers the average ratio of aggressive ROLs, it does not change the "speed" at which the ratio of students with correlation neglect responds to larger biases. The null effect of the reminder treatment is consistent with the findings of Rees-Jones et al.

(2024), where various interventions aimed at improving students' understanding of the correlations in admission probabilities do not eliminate cognitive biases in their school choices. Additionally, our Computation treatment replicates the null effect observed in the lottery treatment of Rees-Jones et al. (2024), where students are provided with probabilities of enrolling in their selected schools and the likelihood of being unmatched. The persistence of substantial biases in both our study and that of Rees-Jones et al. (2024) suggests that correlation neglect in school choice is not easily rectified.

In contrast, switching to an Iterative DA mechanism lowers the rate at which the ratio of aggressive ROLs changes in response to larger biases by 4.8%. It also reduces the risk of being unassigned. This improvement could potentially arise from the nature of the dynamic mechanism, which makes the correlation in admission probabilities more apparent during the decision-making process. As discussed in Bó and Hakimov (2024), the primary advantage of the equilibrium strategy lies in its straightforward mechanics, where agents select their preferred option from a menu rather than submitting a ROL that represents their preferences. Notably, there has been growing interest from policymakers in implementing dynamic college admission mechanisms, as evidenced by recent reforms in college admissions in France, Inner Mongolia, Germany, and Tunisia (Bó and Hakimov, 2022; Gong and Liang, 2024; Luflade, 2018).

This paper contributes to three strands of literature. Firstly, we contribute to the growing literature on correlation neglect. Enke and Zimmermann (2019) show that individuals tend to treat correlated signals as if they were independent. Rees-Jones et al. (2024) explore the implications of correlation neglect with the constrained DA and find that correlation-neglectful agents will be overly aggressive in filling slots in a preference submission. Rees-Jones et al. (2024) has the closest features to our paper. However, we diverge from Rees-Jones et al. (2024) in two notable ways. First, we design the school choice game so that students face uncertainty in admissions due to incomplete information about *others' preferences*. In contrast, the uncertainty is imposed in Rees-Jones et al. (2024) exogenously. Second, we investigate the underlying drivers of correlation neglect and distinguish successful interventions from unsuccessful ones that aim to alleviate the mistakes of correlation neglect.

We also contribute to the burgeoning literature on behavioral market design in school choices. Abundant research has documented preference misrepresentations in strategy-proof mechanisms and proposed candidate theories to explain these misrepresentations, including failures of contingent reasoning, overconfidence, correlation neglect, and more (Rees-Jones and Shorrer, 2023; Dreyfuss et al., 2022; Guillen and Hakimov, 2017; Kapor et al., 2020; Lucas and Mbiti, 2012; Meisner and von Wangenheim, 2023; Pan, 2019; Rees-Jones, 2017; Rees-Jones, 2018a). Despite the abundant empirical evidence and theoretical explanations, there is relatively little research investigating potential remedies, with some recent exceptions. Arteaga et al. (2022) and Larroucau et al. (2024) have implemented field interventions and found that real-time provisions of personalized admission risks can reduce application risk and increase placement rates. Our findings complement this literature and suggest that in addition to information provision, switching the simultaneous mechanism to the iterative mechanism may also help address students' correlation neglect in school choices.

Lastly, we make contributions to the literature on dynamic matching mechanisms. A few recent papers experimentally evaluate various types of iterative mechanisms. Klijn et al. (2019) find no statistically significant difference in the proportion of stable outcomes between the standard and dynamic student-proposing DA. Gong and Liang (2024) find that, compared to DA, the Inner Mongolia mechanism exhibits higher truth-telling rates in the environment with low preference correlation. However, there is a higher proportion of stable outcomes under DA in the high preference correlation environment.[4] Bó and Hakimov (2020) compared two types of IDA with DA: one where students are only informed of the admission outcomes (IDAM-NC) and one where the tentative cutoff values of each college are provided (IDAM). They find that both dynamic mechanisms deliver significantly more stable outcomes than DA. The authors associate the benefits of iterative mechanisms relative to DA with the learning opportunities from the feedback provided between steps of the iterative mechanisms. Our findings complement this literature by suggesting an additional channel through which iterative mechanisms improve matching outcomes in centralized school choices.

[4] It is worth noting that the dynamic mechanism used in Gong and Liang (2024) differs from IDA. Therefore, one might remember that the results here are not directly comparable.

The remainder of the paper is structured as follows. Section 2 outlines the school choice problem and a theoretical framework to identify correlation neglect; we then introduce the experimental design in Section 3. Section 4 presents the main results, and we conclude with Section 5.

2 The school choice problem

2.1 A theoretical framework of correlation neglect

We model the ability to think contingently as a scarce resource. Consider a student i's expected utility U_i is a function of the CN parameter θ, and it is the sum of the following two components: U_c is the expected utility calculated "correctly" with the conditional school admission probabilities, and *bias* is the biased term between the expected utility and the utility calculated "incorrectly" using the unconditional probabilities, thus $bias = U_u - U_c$. Due to failure to think contingently, she perceives the expected utility to be

$$U_i(\theta) = U_c + \theta * bias, \tag{1}$$

where θ is the degree of correlation neglect with $\theta = 0$ as the standard case of no correlation neglect. When $\theta = 1$, she exhibits full correlation neglect.

The correlation neglect parameter, θ, is a function of the salience s of the contingencies and complexity of calculating admission probabilities N. We assume that the correlation neglect θ is decreasing in the salience s and increasing in the complexity N:

$$\theta = \theta(s, N), \quad \frac{\partial \theta}{\partial s} < 0, \quad \frac{\partial \theta}{\partial N} > 0$$

This model closely follows the framework used to study inattention and has clear implications for identifying correlation neglect and designing interventions to alleviate mistakes driven by it (DellaVigna, 2009). We discuss the identification and treatments in detail in the following two subsections.

2.2 The school choice task

We consider a school choice problem with four students and four schools (A, B, C, D) where each school has a capacity of one seat. Students' priorities are determined by their scores on a standard test and they are aware of their own score and ranks. Students' preferences are randomly drawn from Type I ($A \succ B \succ C \succ D$) and Type II ($C \succ D \succ B \succ A$).[5] Students know their own preferences but not other students' preferences. Instead, they are aware of the preference distribution in the student population, namely, the ratio of students with Type I or Type II preference. Students are matched to schools using a constrained DA mechanism with two choices.

Although, in theory, the top two ranked students have no incentive to deviate from truth-telling, it is documented that students often deviate from truth-telling even with strategy-proof mechanisms in practice (Hassidim et al., 2017; Rees-Jones, 2018b; Rees-Jones and Skowronek, 2018; Shorrer and Sóvágó, 2023). To reduce the strategic uncertainties related to the top students, we use computers as the top two ranked students and they are truth-telling throughout the task. We explained this approach clearly to all participants.

Unlike the top students, the third-ranked student has no dominant strategy and must compare the expected utility of different strategies when constructing the optimal ROL. We illustrate this with a numeric example in Table 1. Panel A shows the preference for both types and the probability of a student being Type I. Panel B contrasts the expected payoffs of different strategies. Although an aggressive strategy listing schools C and D may seem optimal when ignoring the correlations of admission probabilities to different schools, accounting for them reveals that combining a reach and a safety school offers the highest payoff.

Our numerical example in Table 1 underscores the fundamental principles in our school choice setups: the admission uncertainty arises from the uncertainty about others' preference types, and the rejection (if it happens) by the school ranked first in the ROL reveals new information about the preference distributions. Failure to think through the possible contingencies leads students to assess their admission chances incorrectly.

[5] This preference setup resembles the common trait in real-world school choice matching markets. Schools A and B can be seen as high-quality but out-of-town schools. Schools C and D may have lower quality but are local. Students' preferences could broadly be classified as those who prefer higher quality (Type I) or those who prefer local schools (Type II).

Table 2 further illustrates this intuition. Panel A lists all three possible contingencies and admission probabilities for the third-ranked student with a Type II preference. Rejection from the top choice (School C) reduces the possible contingencies from all three to only the last two. The unconditional probability of being admitted to School D is $2p*(1-p)+p^2$, higher than the conditional probability of $\frac{2p*(1-p)}{1-p^2}$, regardless of the percentage of students with Type I preference in the population p. Figure 1 compares the admission probabilities to School D for the students that we focus on, conditional (solid line) and unconditional (dashed line) on rejecting by School A. This comparison shows that when students fail to update the possible contingencies when rejected by their top choice, they tend to be overly optimistic about their admission chances in their second-most preferred schools.

We propose to exploit the variation across different rounds in the baseline experiment to identify the existence of CN. To see this, we compare the expected utility between listing School C and D, and School C and B. Following the definition in equation (1) in section 2, the difference in the expected utility of these two strategies is:

$$U_i(\theta)^{CD} - U_i(\theta)^{CB} = (U_c^{CD} - U_c^{CB}) + \theta * \gamma \tag{2}$$

where $U_c^{CD} - U_c^{CB}$ is the differences in the expected utility of these two strategies using conditional probabilities; U_u^{CD} and U_u^{CB} are the expected utility of listing schools CD and CB calculated with unconditional admission probabilities;

$$\gamma = (U_u^{CD} - U_u^{CB}) - (U_c^{CD} - U_c^{CB}) \tag{3}$$

is the bias term induced by correlation neglect; θ is the correlation neglect parameter. Equation (2) shows that, holding the differences in expected utility constant, the larger the bias term, the more likely students with correlation neglect would perceive listing CD as the most favorable option.

In our baseline treatment, students play the school choice problem for 15 rounds. In each round, the school choice environment stays the same while students' preferences and the preference distribution change. As a result, the bias term due to correlation neglect differs in each round.

Table 3 shows how the bias term changes with the preferences and the preference distribution used in each round. Columns 6 and 7 show that listing CB has the highest expected utility in all rounds, and the bias terms differ in each round. As a result, rational students will always choose CB, while students with correlation neglect will choose CD. This variation in the bias allows us to identify the existence of correlation neglect.

This identification strategy is similar to those used to identify inattention in Hossain and Morgan (2006) and Chetty et al. (2009) in the section on alcohol taxes. Hossain and Morgan (2006) compared the average revenue from two auctions using a field experiment. They sell CDs with different reserve prices and shipping costs in two auctions, holding constant the total cost. The change in reserve price guarantees that the two auctions are equivalent to a fully attentive bidder. But if bidders are inattentive, the average revenue should be higher in the auction with lower reserve prices and higher shipping costs. In our experiment, if students have no correlation neglect, the bias term should not impact the ratio of students choosing the aggressive strategy. There is a slight difference between our strategy and those used in Hossain and Morgan (2006). In Hossain and Morgan (2006), the two auctions have identical costs. In different rounds of our experiment, though the optimal strategy is always submitting CB, the differences in expected utility between submitting CB and CD are slightly different. Even though these differences should not affect fully rational students' decision-making, we control them whenever we compare students' strategies across different rounds.

Our Hypothesis 1 summarizes this identification strategy.

Hypothesis 1. *If students exhibit correlation neglect in the school choice task, the bias term should be positively associated with the share of aggressive ROL.*

3 Experimental design

In this section, we use three treatments to address two potential drivers of correlation neglect: the salience of contingencies and the complexity involved in calculating admission probabilities. We adopt a between-subject design, and we describe the treatments below. Instructions are available in the Appendix.

3.1 Treatment groups

Our first treatment is an intervention designed to highlight the correlated admission chances. This **Reminder** treatment shares our baseline group's school choice setup, with one notable exception. We provide students with a message indicating the correlation between being accepted to the second and first choices.

"Hint: Please note the possible correlation between being accepted to the second choice and being accepted to the first choice school."

This message is displayed on the same page where students submit their preferences. Furthermore, we ask students to estimate the probability of getting into the second choice when rejected by the first choice.

"Please estimate the probability that you will be accepted to the second choice of your applications if you are not accepted to the first choice. (1-100)% ."

In our second treatment, we switch to an **Iterative DA (IDA)** mechanism. Unlike the Deferred Acceptance mechanism, where students submit a ROL, IDA asks students to apply to one school at each step. Schools tentatively retain no more applications than their capacity, and if a school receives more applications than it can accept, it rejects the students with lower priorities and retains the remaining applications. After each step, students are informed whether their application was rejected or accepted.[6] If a student is rejected, they can apply to any other school with empty seats or a lower cutoff score. Students are not allowed to change their choices while tentatively selected by any school. For those who get accepted in their first-choice schools, we ask them to fill in the second choice as if the first choice rejected them.

[6] In real-world applications, IDA may provide students with the cutoff information after each step. In our setup, this information is redundant; therefore, we do not provide the cutoff information to students.

Unlike the standard DA mechanism, IDA does not have a dominant strategy, and the Student Optimal Stable Matching is an equilibrium outcome under Ordinal Perfect Bayesian Equilibrium (Bó and Hakimov, 2022). While IDA has "worse" incentive properties for students than DA, in practice, students might benefit from the iterative nature of the game. Participants might find these procedures simpler to understand or more transparent. Bó and Hakimov (2020) experimentally compare the IDA with DA and find that a significantly higher proportion of stable outcomes is reached under the IDA. They associate the benefits of iterative mechanisms with the feedback on the outcome of the previous application they provide to students between steps. In our **IDA** treatment, we focus on another channel where the iterative mechanisms may help students in centralized school choices. The iterative nature of IDA may render the correlation nature of our school choice environments highly salient.

To summarize, if the reminder messages and the adoption of the IDA mechanism make the correlation in admissions more salient, these treatments should reduce the rate at which the ratio of students submitting aggressive ROLs increases in response to larger biases. We summarize these results in the following hypothesis.

Hypothesis 2. *If $\frac{\partial \theta}{\partial s} < 0$, the Reminder and IDA treatments should reduce the rate at which the ratio of students submitting aggressive ROL in response to larger biases compared to the baseline results.*

Both Reminder and IDA treatments focus on helping students consider the salience of the correlated admission probabilities. However, given the complexity of the school choice environment, it is still a challenging task for students to report the optimal ROL. One significant hurdle is that students must perform the Bayesian updating calculations to realize that choosing Schools C and D is not the optimal strategy. To address this issue, we designed a **Computation** treatment that provides students with individualized calculations of admission probabilities for all possible application strategies. As assumed in the model, $\frac{\partial \theta}{\partial N} > 0$, the computation treatment should help students with correlation neglect to avoid aggressive strategies.

Hypothesis 3. *If $\frac{\partial \theta}{\partial N} > 0$, the Computation treatment should lower the speed with which the ratio of students submitting aggressive ROL in response to larger biases, compared to the baseline results.*

3.2 Experimental procedures

We conducted the experiment in the Smith Economics Experimental Center laboratory at Shanghai Jiaotong University in China. Participants were undergraduate and graduate students from this university. A total number of 217 subjects participated in 14 online sessions between 2021 and 2023. Each session lasted approximately one hour, with participants receiving an average payment of 40.96 yuan, including the show-up fee. We programmed the experiment with oTree (Chen et al., 2016).

Table 4 outlines the procedures and timeline of the experiment. The first part involves the standard school choice problem. To assess contingent thinking abilities, we adopted the measures for Bayesian updating (BU) and non-probabilistic reasoning (NPR) from Levin et al. (2016). Unlike Levin et al. (2016), we did not differentiate between BU and NPR skills; instead, we created a proxy for contingent thinking by combining all four questions. We also followed the methodology of Holt and Laury (2002) to assess each subject's risk attitude and ambiguity aversion. Finally, we collected demographic information, details about participants' past college application experiences, and their attitudes toward general college application strategies in the post-survey.

Table 5 presents the summary statistics for students' demographic characteristics, risk attitudes and ROL types by treatments. Participants in the baseline group tend to be slightly older and more likely to be female and graduate students than those in the three treatment groups. This may be due to the narrow age range of 18 to 25.[7] Table 5 shows no significant difference across the groups regarding risk aversion and contingent thinking abilities. As shown in Figure 1, we set up the school choice experiments so that selecting Schools C and B is always the optimal strategy in each experiment round. Based on this, we categorize students' strategies into three types: optimal ROL with Schools C and B, aggressive ROL with Schools C and D, and other strategies. The third panel in Table 5 reveals that a significant proportion of students make behavioral mistakes and choose the aggressive strategy, resulting in about 5 percent of students remaining unassigned.

[7] We should not worry about the small imbalance between treatments since we control for all observed individual characteristics in our regression analysis in later sections.

4 Results

4.1 Identification of correlation neglect

We first present the cognitive biases caused by correlation neglect. Hypothesis 1 suggests that we should observe a higher share of aggressive ROL in rounds with larger biases. Figure 2 illustrates the relationship between the share of aggressive ROLs and the size of the bias term in each round of baseline treatment, revealing a strong positive correlation.

To quantify this relationship, we estimate the following empirical specification:

$$y_{it} = \alpha + \beta_1 * bias_t + \beta_2 * X_{it} + \delta_i + \lambda_{it} + \varepsilon_{it}, \tag{4}$$

where y_{it} denotes the admission outcomes, including whether a student submits an aggressive ROL or is unassigned to her ROL; the $bias_t$ measures the size of the bias γ defined in Eq (2) in Section 2. Here, the subscripts i, t denote the individual and round, respectively. X_{it} includes subjects' demographics, such as age, gender, risk aversion, ambiguity aversion, and contingent thinking ability. δ_i and λ_{it} denote the session and round fixed effects, respectively. ε_{it} is the residual.

Table 6 reports the estimation results of Eq (4). The first column quantifies the visual pattern observed in Figure 2. Column (2) repeats this exercise with more demographic variables, including measures of risk aversion, ambiguity aversion, contingent thinking ability, and round and session fixed effects. In both model specifications, the bias term significantly increases the share of aggressive ROL. One standard deviation increase in the bias leads to about 17% more mistakes in ROL.[8] Additionally, being male, students with lower NCEE scores, and low contingency thinking ability are correlated to more correlation neglect. We find similar results in columns (3) and (4) with observations in all four treatments.

We also consider the risks of being unassigned in columns (5) to (8) in Table 6. We expect to observe fewer unassigned students in rounds with smaller biases. We use whether a student is unassigned to her ROL as the dependent variable. Students are less likely to be unassigned in

[8] The standard deviation of the bias term in the baseline sample is 10.5584. One standard deviation increase in the bias leads to 10.5584*0.0114=0.1203, a 12 percentage points increase in the proportion of aggressive ROLs. This represents a 17% increase, relative to the ratio of aggressive ROLs in the baseline group.

rounds with smaller biases. Specifically, a one standard deviation decrease in the bias leads to about a 25% reduction in the ratio of unassigned students in the baseline group.[9]

One concern is that students might adapt to the bias if they learn from the admission outcomes of previous rounds. For example, an unassigned student ceases to adopt an aggressive strategy in the subsequent round. If this is the case, the reduction in the rate of mistakes is due to her past experience, not the bias *per se*. We find this is not the case. To see this, we plot the share of aggressive ROL by round and treatment group in Figure 3. The share of aggressive ROL does not exhibit a declining trend across rounds.

4.2 Treatment effects

We proceed to examine our treatments' impacts of different interventions. We use the following empirical specification to examine the treatments' effects:

$$y_{it} = \alpha + \beta_1 * Treatment_i + \beta_2 * bias_t + \beta_3 * Treatment_i * bias_t + \beta_4 * X_{it} + \delta_i + \lambda_{it} + \varepsilon_{it} \quad (5)$$

The notations y_{it}, $bias$, X_{it}, δ_i, γ_t and ε_{it} are consistent with Eq. (4), where the subscripts i, t denote the individual and round, respectively. We adopt a between-subject design so that treatments do not vary by session.

The parameter of interest is β_3. Hypotheses 2 and 3 suggest that if our treatments make the correlation in admission probabilities more salient and reduce computational complexity, we should observe a negative β_3.

Table 7 presents these results separately for each of the three treatments. Columns (1) and (3) show that the Reminder and Computation treatments have negligible effects on students' decision-making, with the coefficients for the interaction term being both economically and statistically insignificant. In contrast, Column (2) reports a significant impact of the IDA treatment on reducing the proportion of students making aggressive school choices. β_3 is significantly negative at the 1% significance level. $\beta_3 = -0.0015$, given that the mean value of bias in the baseline and IDA groups is 32.2967, it translates to a 4.8 percent reduction of the share of aggressive ROL at the mean

[9]Following the last footnote, the percentage is calculated as -0.0013*10.5527/0.054=-0.2540.

compared to the baseline results.

The null effect of the *Reminder* treatment is consistent with Rees-Jones et al. (2024), where multiple treatments targeted to improve students' awareness of the correlations in admission probabilities failed to remove the bias in students' school choices. Moreover, our *Computation* treatment replicates the findings of null effect from the lottery treatment in Rees-Jones et al. (2024) where they provide students with probabilities of enrolling in students' choices and the probability of being unmatched. The fact that quantitatively large bias remains in the two different environments that our paper and Rees-Jones et al. (2024) suggests that the correlation neglect in the school choice context cannot be easily eliminated.

Our findings suggest that reducing the complexity of computing conditional probabilities helps prevent students from making aggressive ROLs. However, this decrease in aggressive behaviour is not due to increased awareness of admission correlations, as the interaction between the Computation treatment and the bias term does not significantly affect the likelihood of choosing aggressive ROLs. Therefore, our results indicate that simplifying the computation process may correct behavioral biases in making aggressive school choices unrelated to correlation neglect.

In contrast, the results from the *IDA* treatment suggest that the iterative mechanisms could effectively reduce correlation neglect in school choices. We argue that this improvement arises from the nature of the dynamic mechanism, which makes the correlation in admission probabilities more apparent to students in the decision-making process. As discussed in Bó and Hakimov (2024), the simple mechanics of the equilibrium strategy, in which agents "pick" the object they would like to have from a menu, instead of submitting a ranking of objects representing their preferences, is the main driver of the superior. Interestingly, there has been increasing demand from policymakers for the use of dynamic college admission mechanisms, e.g., recent reforms of college admissions in France, Inner-Mongolia, Germany, and Tunisia (Bó and Hakimov, 2022; Gong and Liang, 2024; Luflade, 2018).

5 Concluding remarks

Our paper examines correlation neglect, a specific type of non-standard decision-making (DellaVigna, 2009). This concept applies to various areas such as stock return predictions (Cohen and Frazzini, 2008), financial investments (Hong and Stein, 1999; Huberman and Regev, 2001), voting behavior (Levy and Razin, 2015), auctions (Hossain and Morgan, 2006), and school choices (Ali and Shorrer, 2021; Rees-Jones et al., 2024). In the college application process, where students select a limited number of schools from a long list, they commonly neglect the correlation between admission probabilities. We investigate whether students exhibit correlation neglect (CN) in a laboratory setting and explore possible interventions to reduce this cognitive bias. Our study would shed light on the design of such college admissions processes, potentially impacting over 23% of the world population (World Bank, 2022) in countries such as Australia, Chile, China, Germany, Greece, Hungary, Ireland, Russia, Spain, Turkey, and the United Kingdom (Chen et al., 2020).

We designed a school choice experiment under a constrained DA system, where students could choose two out of four schools based on their preferences. In our experiment, students who experience correlation neglect prefer a more aggressive strategy. We introduce cognitive bias in each round of the experiment and use variations in school choices to identify correlation neglect. Our design closely mirrors the real-world school application problem, where students face uncertainty in admissions due to incomplete information about others' preferences, even though they are fully informed of their own test scores and rankings. Furthermore, we design and test three different interventions to reduce decision-making mistakes caused by correlation neglect. These interventions aim to make cognitive bias more salient and simplify the calculation of accurate admission correlations.

Our estimation results show that reminding students of the correlation between school admissions has little impact on the proportion of students making aggressive school choices. On the other hand, reducing the complexity of computing conditional probabilities significantly helps prevent students from deviating from their optimal choices, although this reduction in aggressive behavior is not due to increased awareness of admission correlations. The Iterative DA mechanism, however, effectively reduces correlation neglect in school choices as it informs students of the admission results after submitting their ROLs by order. Interestingly, there is an increasing demand from policymakers for the use of dynamic college admission mechanisms in real-world applications. This trend is evident in recent college admissions reforms of college admissions in France, Inner Mongolia, Germany, and Tunisia (Bó and Hakimov, 2022; Gong and Liang, 2024; Luflade, 2018).

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Figures and tables

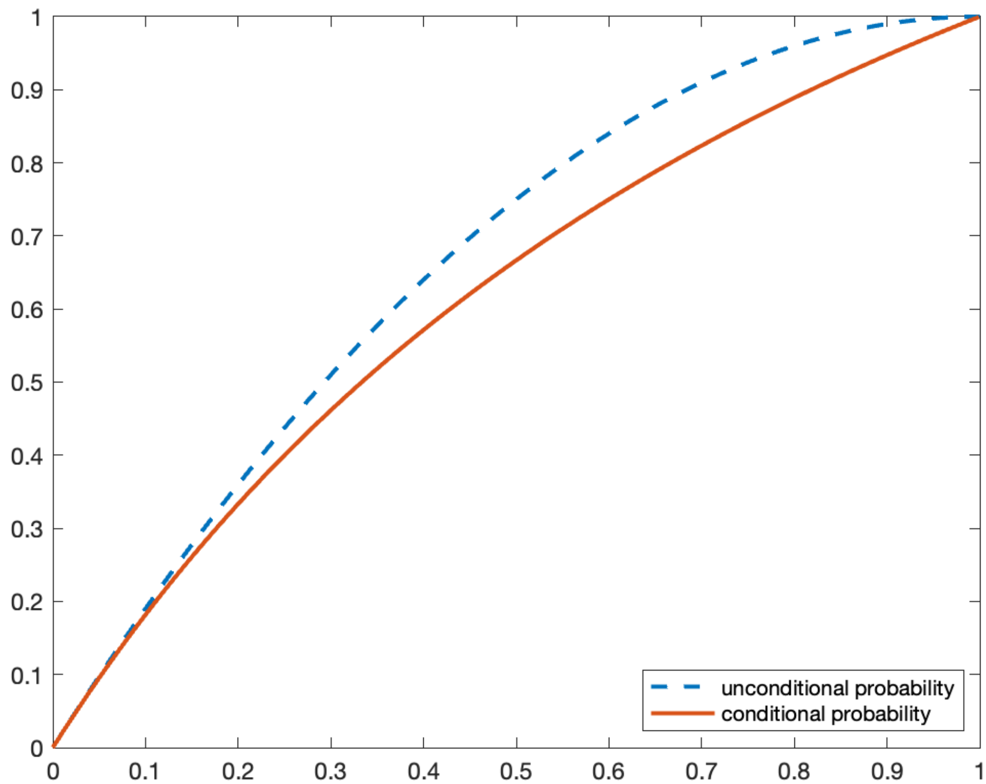

Figure 1: Comparison between the unconditional and conditional probability of admission

Note: This figure compares the probability of admission to School D for the student ranked third with type II preference. The x-axis is the percentage of students with type I preference in the student population. The y-axis is the admission probability.

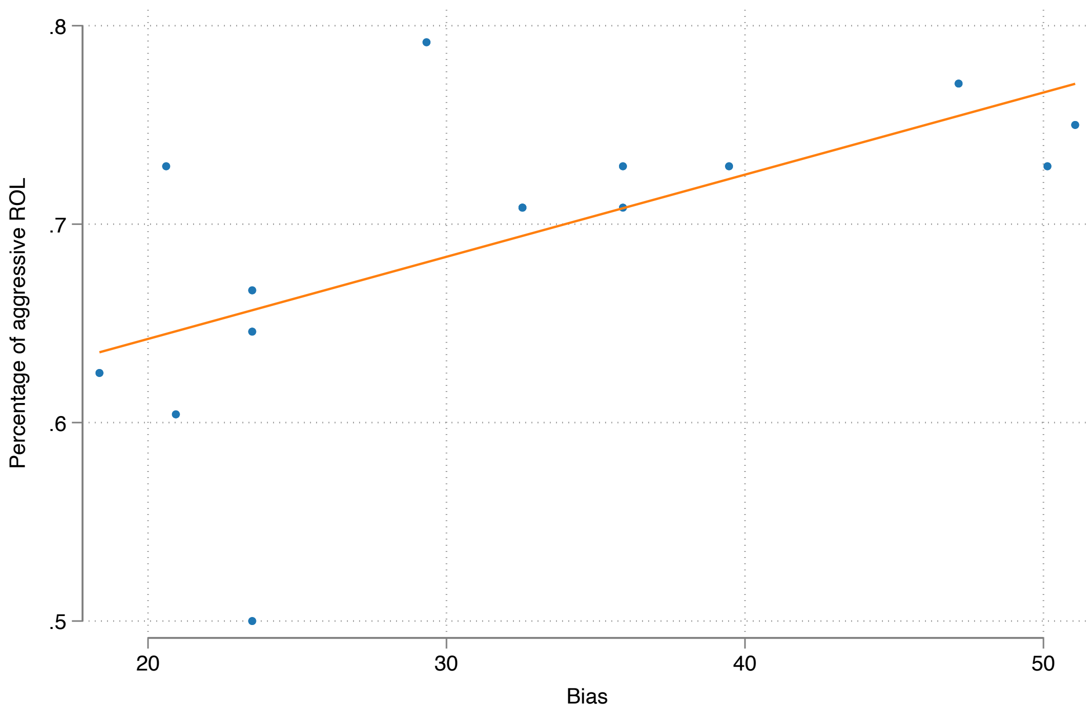

Figure 2: The size of the bias and share of aggressive ROL in the Baseline group

Note: This figure plots the percentage of aggressive ROL in each round against the size of the bias in each round of school choice setup in our baseline group. The bias term is calculated as $bias = (u(cd)_u - u(cb)_u) - (u(cd)_c - u(cb)_c)$ The aggressive ROL is defined as listing both school C and D.

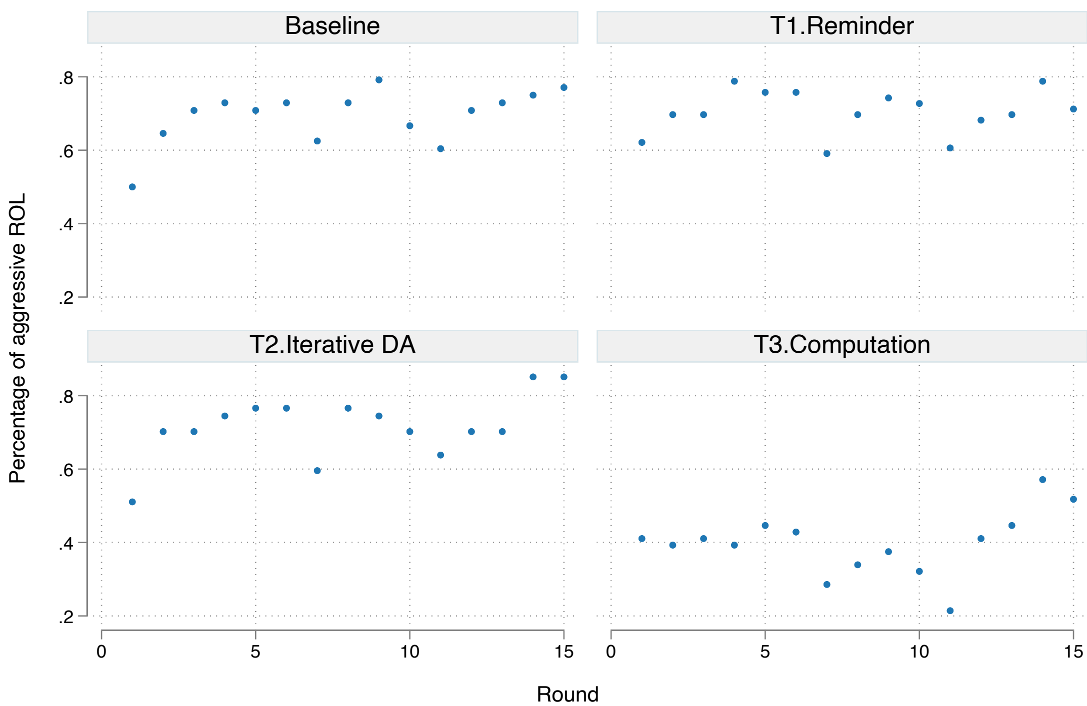

Figure 3: The share of aggressive ROL by round and treatment group

Note: This figure plots the percentage of aggressive ROL in each round. The aggressive ROL is defined as listing both school C and D.

Table 1: A Numerical example of correlation neglect

Panel A: Setup									
	Type I preference				Type II preference				Ratio of Type I
School	A	B	C	D	C	D	B	A	
Utility	100	45	40	10	100	45	40	10	70%
Panel B: Expected utility for the student ranked third									
ROL	CD	CB	CA	DB	DA	BA			
Unconditional	**89.95**	69.4	40.9	61.35	41.85	21.30			
Conditional	86.06	**89.00**	50.76	80.95	50.95	20.40			

Note: Panel A shows the utility of being admitted to each school for both Type I and II. The first row in Panel B lists all possible ROLs with two schools. The second and the third row report the expected utility of the corresponding ROL calculated using the unconditional and conditional probabilities, respectively. The conditioning event is rejection from the school listed first.

Table 2: Possible contingencies and admission probability for the student ranked third with type II preference

Panel A: Possible contingencies			
Contingency	Types of top 2 students	Probability	Seats taken
1	Both type I	p^2	A and B
2	Type I and II	$2p * (1-p)$	A and C
3	Both type II	$(1-p)^2$	C and D
Panel B: Admission probabilities			
Conditional probability	$p(D \mid rejC) = \frac{2p*(1-p)}{1-p^2}$	$p(B \mid rejC) = 1$	
Unconditional probability	$p(D) = 2p * (1-p) + p^2$	$p(B) = 1 - p^2$	

Note: Panel A presents all three possible scenarios of the top 2 students' types. Panel B shows the conditional and unconditional probabilities of being admitted to School D and School B, respectively. p is the percentage of students with type I preference.

Table 3: The school choice setup for each round of the experiment

Round	**School payoffs**				**Ratio of Type I**	**Expected utility differences**	**Bias**
	A	B	C	D		$U_c^{CB} - U_c^{CD}$	
1	10	40	100	45	0.7	2.94	23.49
2	10	40	95	45	0.7	2.94	23.49
3	10	50	120	55	0.75	2.86	32.54
4	10	50	95	55	0.8	1.11	35.91
5	10	50	90	55	0.8	1.11	35.91
6	10	55	100	60	0.8	1.67	39.47
7	10	35	100	40	0.65	3.48	18.37
8	10	35	100	40	0.7	2.06	20.61
9	10	45	95	50	0.75	2.14	29.33
10	10	40	95	45	0.7	2.94	23.49
11	10	40	120	45	0.65	4.55	20.93
12	10	50	100	55	0.75	2.86	32.54
13	10	70	120	75	0.8	3.33	50.13
14	10	65	100	70	0.85	0.68	51.06
15	10	60	90	65	0.85	0.27	47.16

Note: This table shows the school choice setups in each round of the experiment. The ratio of Type I is the ratio of students with Type I preference in the population. U_u^{CD} is the expected utility of choosing School C and D calculated with unconditional admission probability. U_c^{CD} is the expected utility of choosing School C and D calculated with conditional admission probability. The expected utility differences using conditional probabilities between strategies CB and CD is defined as $U_c^{CB} - U_c^{CD}$. The bias term in the last column is defined as $U_u^{CD} - U_u^{CB}) - (U_c^{CD} - U_c^{CB})$

Table 4: Timeline of treatment groups in the experiment

Treatments	Part 1	Part 2	Part 3	Part 4
Baseline	15 rounds of task	CT/IQ test	Risk/Ambiguity attitude	Survey
Reminder	Task and nudge messages	CT/IQ test	Risk/Ambiguity attitude	Survey
Iterative DA	Two rounds of submissions	CT/IQ test	Risk/Ambiguity attitude	Survey
Computation	Task and probabilities	CT/IQ test	Risk/Ambiguity attitude	Survey

Note: We adopt a between-subject design. Contingent thinking ability (CT) is measured by the answers to four questions in Levin et al. (2016). We construct the proxy of IQ using the Raven's advanced progressive matrices. Risk-aversion is measured by the switch point following the classic Holt and Laury (2002) task, the later one switches the more risk aversion she is; so is ambiguity aversion. We collect their person characteristics, historical college application experience, and their attitude towards the general strategies to apply to colleges.

Table 5: Summary statistics of subjects' ROL types and demographics

	Baseline	T1.Reminder		T2.Iterative DA		T3.Computation	
	Level	Level	Difference	Level	Difference	Level	Difference
Age	22.69	21.92	0.763***	22.17	0.517***	21.88	0.813***
Male (%)	0.48	0.56	-0.081***	0.64	-0.159***	0.50	-0.021
Undergraduates (%)	0.31	0.56	-0.08***	0.49	-0.177***	0.50	-0.188***
NCEE score	611.85	636.53	-24.676***	588.13	23.727***	601.66	10.193*
Risk aversion (0-10)	7.15	6.95	0.191*	6.98	0.167*	7.20	-0.051
Contingent score	0.77	0.86	-0.093*	0.85	-0.08	0.91	-0.14***
Ambiguity aversion	12.56	12.53	0.032	11.94	0.626**	12.48	0.080
CD (%)	0.69	0.70	-0.011	0.72	-0.023	0.40	0.295***
CB (%)	0.22	0.24	-0.022	0.22	-0.000	0.55	-0.330***
Other (%)	0.08	0.05	0.033***	0.06	0.024*	0.05	-0.035***
Unassigned (%)	0.05	0.04	0.015	0.04	0.012	0.03	0.020*
Num. of Obs.	720	990	-	705	-	840	-

Note: This table presents the summary statistics of students' demographics, strategies and outcomes in the school choice experiments, by treatment groups. The NCEE score is student's test score in China's college entrance exam. The risk attitude and ambiguity aversion are measured following Holt and Laury (2002). The contingent ability is constructed as summing up the scores for all four questions in Levin et al. (2016). We test the significance of the mean differences between the Baseline group and each treatment group using t statistics and present the corresponding significance level with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: The size of the bias induced by correlation neglect and share of aggressive ROL

	Aggressive ROL				Unassigned			
	Baseline group		All groups		Baseline group		All groups	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
bias	0.0041*	0.0114**	0.0048***	0.0080***	-0.0020*	-0.0013***	-0.0015***	-0.0026***
	(0.0016)	(0.0038)	(0.0008)	(0.0018)	(0.0008)	(0.0000)	(0.0003)	(0.0000)
Male		0.1974***		0.0790***		0.0342		0.0001
		(0.0398)		(0.0172)		(0.0215)		(0.0064)
NCEE score		-0.0008***		-0.0002**		-0.0000		0.0000
		(0.0002)		(0.0001)		(0.0001)		(0.0000)
Age		0.0086		-0.0016		-0.0048		-0.0009
		(0.0096)		(0.0045)		(0.0054)		(0.0022)
Risk aversion		0.0006		-0.0162***		-0.0008		0.0003
		(0.0101)		(0.0045)		(0.0077)		(0.0016)
Ambiguity aversion		0.0053		0.0038*		0.0006		-0.0002
		(0.0033)		(0.0015)		(0.0018)		(0.0007)
Contingent thinking ability		-0.0752***		-0.0387***		-0.0114		-0.0045
		(0.0206)		(0.0085)		(0.0110)		(0.0033)
Round & Session FE		✓		✓		✓		✓
R^2	0.009	0.097	0.011	0.124	0.009	0.033	0.007	0.014
N	720	720	3255	3255	720	720	3255	3255
Dep. mean	0.693	0.693	0.625	0.625	0.054	0.054	0.042	0.042

Note: This table presents the size of the bias in each round of school choice setup in our baseline group affect students' strategy in submitting ROLs. The bias term is formally defined as $bias = (u(cd)_u - u(cb)_u) - (u(cd)_c - u(cb)_c)$. The NCEE score is student's test score in China's college entrance exam. The risk attitude and ambiguity aversion are measured following Holt and Laury (2002). The contingent ability is constructed as summing up the scores for all four questions in Levin et al. (2016). Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Effects of interventions designed to alleviate correlation neglect

	Aggressive ROL		
	(1)	(2)	(3)
Bias	0.0075**	0.0121*	0.0063*
	(0.0025)	(0.0006)	(0.0025)
T1.Reminder	0.1583		
	(0.1284)		
T1.Reminder # *bias*	-0.0007		
	(0.0018)		
T2.Iterative DA		-0.0340	
		(0.0425)	
T2.Iterative DA # *bias*		-0.0015***	
		(0.0000)	
T3.Computation			-0.8991***
			(0.1362)
T3.Computation # *bias*			0.0026
			(0.0022)
Round & session FE	✓	✓	✓
Demographic controls	✓	✓	✓
Observations	1710	1695	1560
R-squared	0.070	0.181	0.149

Note: This table presents the effects of treatments designed to alleviate mistakes due to correlation neglect. The bias term is formally defined as $bias = (u(cd)_u - u(cb)_u) - (u(cd)_c - u(cb)_c)$. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Online appendix: Experimental instructions

Baseline

Task Description: This part of the experiment is to fill out an admission application. In this task, in each round, there are four schools for four students to choose from and one person is admitted to each school, while you as one of the students will choose and fill in the form among the four schools. Each student's preferences (favorites) for the four schools are randomly assigned by the computer with a certain probability, and each person's preferences are independent, i.e., your favorite school does not change because of the others' favorites; the school chooses the student with the highest score. In each round of the school choice experiment, you make your choice of schools based on your preferences and in combination with others, filling in what you think is the best. At the end of each round, you will learn your admissions results, and students who drop out (i.e., are not admitted to the school of their choice) will be admitted to the school with the same payoff as the last-place school under that student's preference. There are twenty rounds of applications in total, each round being independent and having no effect on each other.

The next experimental process takes place in fixed groups of four, and there are 20 rounds, with your performance ranked in the third place in each round. Different rounds of the experiment are conducted independently, i.e., the payoffs in each round are independent. We will randomly select one of the 20 rounds of payoff as your gain in this task. At the same time, you can see the payoff you can get by being accepted to each school under your preference. In the experiment, you will know the probability (p) of which preference the student in the top two is. In this part of the experimental task, the first- and second-place students are served by a computer that will choose the top two schools under that preference in order according to the preference they are assigned (realized with probability p).

The decision you need to make in this experiment is to fill out the application based on your own ranking and preference, and the probability of other people's preferences. You can fill in two different first and second school choices at the same time, but the preference for the first choice is required to be higher than the second, i.e., in the case of school choice preference type 1 (see the table below), the first and second volunteers can be school A and school B, respectively; and cannot be school B and school A, respectively. The four schools choose the highest ranking among candidates who declare the same volunteer and do not consider that this is the candidate's first choice: The principle of parallel admission.

Four schools: School A, School B, School C and School D.

Admission rules: the principle of the Chinese parallel admission.

School Choice Preferences: There are two school choice preferences, as shown in the following table:

School choice preference Type 1	**School choice preference Type 2**
School A > School B > School C > School D	School C > School D > School B > School A

In each round of the experiment you will know the school choice preference you were assigned, but only the probability that the top two students are of which school choice preference. Your admission to the school ranked first in your school choice preference brings the highest benefit, the second school brings the next highest benefit, the third school brings the next highest benefit, and the fourth school (the guaranteed school) brings the last benefit. At the beginning of each round of decision-making, the computer randomly assigns your preferences. In each of these 20 rounds of the experiment, your school choice preferences, gains, and the probability of other students' school choice preferences may be different. The acceptance results and gains for each round are revealed at the end of that round so that you can know for each round whether you were accepted to the school you volunteered for and the corresponding gains. Again, it is important to emphasize that the only gains from the 20 rounds are the randomly selected rounds that are your gains from the experiment in this section. The exchange rate of experiment points to cash is 3:1. In addition you will receive a ¥10 show-up fee.

Admission mechanism details: Suppose Amy's school choice preference is preference 1 (school A > school B > school C > school D), and also suppose she ranks first in a group of four. If she fills in the first preference for school A and the second preference for school B (hereinafter referred to as "school A and school B"), she will be admitted to school A with the gain of S(A); if she fills in school B and school C, she will be admitted to school B with the gain of S(B); if she fills in school

C and school D, she will be admitted to school C with the gain of S(B); if she fills in school B and school C, she will be admitted to school D with the gain of S(B). If she fills in school C and school D, she will be admitted to school C, and the gain is S(C), and so on.

The third-ranked Bob and the first-ranked Amy also have school choice preference 1 (school A > school B > school C > school D), and Amy chooses school A and school B, and Bob chooses school B and school C. At this time, for the second-ranked Carl, if he fills in school A and school B, he will be admitted by school B in the next place, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B). B and gain S(B).

Next, to confirm that you understand our experiment description and rules, you will do a simple test that will not be correlated with the experiment gains, but simply to make sure that your reading comprehension of the game rules is not biased. All results in the experiment will be anonymous and we will keep your decisions in this task strictly confidential. If you have any questions, please raise your hand to one of our experiment assistants and they will answer your questions as soon as possible. Please have a calculator ready if needed.

Now for round 1/20 application:

You are school preference type 1 in this round of the school choice experiment.

The admission gain for preference 1 is school A (300)) > school B (20) > school C (15) > school D (0)

You are ranked third in a group of four (with the computer in fourth place).

There is a 75% probability that the top two ranked students have preference 1.

Please choose two schools as your choice of volunteer (note: two options can not be repeated), four schools will follow the principle of parallel volunteering to choose the highest score, your admission results will determine the benefits of your experiment in this round.

Your first choice is

A. School A

B. School B

C. School C

D. School D

Your second choice is

A. School A

B. School B

C. School C

D. School D

Reminder

Task Description: This part of the experiment is to fill out an admission application. In this task, in each round, there are four schools for four students to choose from and one person is admitted to each school, while you as one of the students will choose and fill in the form among the four schools. Each student's preferences (favorites) for the four schools are randomly assigned by the computer with a certain probability, and each person's preferences are independent, i.e., your favorite school does not change because of the others' favorites; the school chooses the student with the highest score. In each round of the school choice experiment, you make your choice of schools based on your preferences and in combination with others, filling in what you think is the best. At the end of each round, you will learn your admissions results, and students who drop out (i.e., are not admitted to the school of their choice) will be admitted to the school with the same payoff as the last-place school under that student's preference. There are twenty rounds of applications in total, each round being independent and having no effect on each other.

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School A > School B > School C > School D	School C > School D > School B > School A

In each round of the experiment you will know the school choice preference you were assigned, but only the probability that the top two students are of which school choice preference. Your admission to the school ranked first in your school choice preference brings the highest benefit, the second school brings the next highest benefit, the third school brings the next highest benefit, and the fourth school (the guaranteed school) brings the last benefit. At the beginning of each round of decision making, the computer randomly assigns your preferences. In each of these 20 rounds of the experiment, your school choice preferences, gains, and the probability of other students' school choice preferences may be different. The acceptance results and gains for each round are revealed at the end of that round, so that you can know for each round whether you were accepted to the school you volunteered for and the corresponding gains. Again, it is important to emphasize that the only gains from the 20 rounds are the randomly selected rounds that are your gains from the experiment in this section. The exchange rate of experiment points to cash is 3:1. in addition you will receive a ¥10 show-up fee.

Admission mechanism details: Suppose Amy's school choice preference is preference 1 (school A > school B > school C > school D), and also suppose she ranks first in a group of four. If she fills in the first preference for school A and the second preference for school B (hereinafter referred to as "school A and school B"), she will be admitted to school A with the gain of S(A); if she fills in school B and school C, she will be admitted to school B with the gain of S(B); if she fills in school C and school D, she will be admitted to school C with the gain of S(B); if she fills in school B and

school C, she will be admitted to school D with the gain of S(B). If she fills in school C and school D, she will be admitted to school C, and the gain is S(C), and so on.

The third-ranked Bob and the first-ranked Amy also have school choice preference 1 (school A > school B > school C > school D), and Amy chooses school A and school B, and Bob chooses school B and school C. At this time, for the second-ranked Carl, if he fills in school A and school B, he will be admitted by school B in the next place, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B). B and gain S(B).

Next, to confirm that you understand our experiment description and rules, you will do a simple test that will not be correlated with the experiment gains, but simply to make sure that your reading comprehension of the game rules is not biased. All results in the experiment will be anonymous and we will keep your decisions in this task strictly confidential. If you have any questions, please raise your hand to one of our experiment assistants and they will answer your questions as soon as possible. Please have a calculator ready if needed.

Now for round 1/20 application:

You are school preference type 1 in this round of the school choice experiment.

The admission gain for preference 1 is school A (300) > school B (20) > school C (15) > school D (0)

You are ranked third in a group of four (with the computer in fourth place).

There is a 75% probability that the top two ranked students have preference 1.

Please choose two schools as your choice of volunteer (note: two options can not be repeated), four schools will follow the principle of parallel volunteering to choose the highest score, your admission results will determine the benefits of your experiment in this round.

Hint: Please note the possible correlation between being accepted to the second choice and being accepted to the first choice school.

Please estimate the probability that you will be accepted to the second choice of your applications if you are not accepted to the first choice. (1-100)% ______.

Your first choice is

A. School A

B. School B

C. School C

D. School D

Your second choice is

A. School A

B. School B

C. School C

D. School D

Iterative DA

Task Description: This part of the experiment is to fill out an admission application. In this task, in each round, there are four schools for four students to choose from and one person is admitted to each school, while you as one of the students will choose and fill in the form among the four schools. Each student's preferences (favorites) for the four schools are randomly assigned by the computer with a certain probability, and each person's preferences are independent, i.e., your favorite school does not change because of the others' favorites; the school chooses the student with the highest score. In each round of the school choice experiment, you make your choice of schools based on your preferences and in combination with others, filling in what you think is the best. At the end of each round, you will learn your admissions results, and students who drop out (i.e., are not admitted to the school of their choice) will be admitted to the school with the same payoff as the last-place school under that student's preference. There are twenty rounds of applications in total, each round being independent and having no effect on each other.

The next experimental process takes place in fixed groups of four, and there are 20 rounds, with your performance ranked in the third place in each round. Different rounds of the experiment are conducted independently, i.e., the payoffs in each round are independent. We will randomly select one of the 20 rounds of payoff as your gain in this task. At the same time, you can see the payoff you can get by being accepted to each school under your preference. In the experiment, you will know the probability (p) of which preference the student in the top two is. In this part of the experimental task, the first and second place students are served by a computer that will choose the top two schools under that preference in order according to the preference they are assigned (realized with probability p).

The decision you need to make in this experiment is to fill out the application based on your own ranking and preference, and the probability of other people's preferences. You can fill in two different first and second school choices, respectively; but the preference for the first choice is required to be higher than the second, i.e., in the case of school choice preference type 1 (see the table below), the first and second volunteers can be school A and school B, respectively; and cannot be school B and school A, respectively. The four schools choose the highest ranking among

candidates who declare the same volunteer, and do not consider that this is the candidate's first choice: The principle of parallel admission.

Four schools: School A, School B, School C and School D.

Admission rules: the principle of the Chinese parallel admission.

School Choice Preferences: There are two school choice preferences, as shown in the following table:

School choice preference Type 1	**School choice preference Type 2**
School A > School B > School C > School D	School C > School D > School B > School A

In each round of the experiment you will know the school choice preference you were assigned, but only the probability that the top two students are of which school choice preference. Your admission to the school ranked first in your school choice preference brings the highest benefit, the second school brings the next highest benefit, the third school brings the next highest benefit, and the fourth school (the guaranteed school) brings the last benefit. At the beginning of each round of decision making, the computer randomly assigns your preferences. In each of these 20 rounds of the experiment, your school choice preferences, gains, and the probability of other students' school choice preferences may be different. The acceptance results and gains for each round are revealed at the end of that round, so that you can know for each round whether you were accepted to the school you volunteered for and the corresponding gains. Again, it is important to emphasize that the only gains from the 20 rounds are the randomly selected rounds that are your gains from the experiment in this section. The exchange rate of experiment points to cash is 3:1. in addition you will receive a ¥10 show-up fee.

Admission mechanism details: Suppose Amy's school choice preference is preference 1 (school A > school B > school C > school D), and also suppose she ranks first in a group of four. If she fills in the first preference for school A and the second preference for school B (hereinafter referred to as "school A and school B"), she will be admitted to school A with the gain of S(A); if she fills in school B and school C, she will be admitted to school B with the gain of S(B); if she fills in school C and school D, she will be admitted to school C with the gain of S(B); if she fills in school B and

school C, she will be admitted to school D with the gain of S(B). If she fills in school C and school D, she will be admitted to school C, and the gain is S(C), and so on.

The third-ranked Bob and the first-ranked Amy also have school choice preference 1 (school A > school B > school C > school D), and Amy chooses school A and school B, and Bob chooses school B and school C. At this time, for the second-ranked Carl, if he fills in school A and school B, he will be admitted by school B in the next place, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B). B and gain S(B).

Next, to confirm that you understand our experiment description and rules, you will do a simple test that will not be correlated with the experiment gains, but simply to make sure that your reading comprehension of the game rules is not biased. All results in the experiment will be anonymous and we will keep your decisions in this task strictly confidential. If you have any questions, please raise your hand to one of our experiment assistants and they will answer your questions as soon as possible. Please have a calculator ready if needed.

Now for round 1/20 application:

You are school preference type 1 in this round of the school choice experiment.

The admission gain for preference 1 is school A (300) > school B (20) > school C (15) > school D (0)

You are ranked third in a group of four (with the computer in fourth place).

There is a 75% probability that the top two ranked students have preference 1.

Please choose two schools in two steps (Note: two choices can not be the same), four schools will follow the principle of parallel admission to choose the highest rank, your admission results will determine the benefits of your experiment in this round.

Your first choice is

A. School A

B. School B

C. School C

D. School D

You have not been accepted to the first choice of schools, please select your second choice

(Or you have been accepted by your first choice! Now, how would you choose your second choice were you not accepted to your first choice?)

Your second choice is

A. School A

B. School B

C. School C

D. School D

Computation

Task Description: This part of the experiment is to fill out an admission application. In this task, in each round, there are four schools for four students to choose from and one person is admitted to each school, while you as one of the students will choose and fill in the form among the four schools. Each student's preferences (favorites) for the four schools are randomly assigned by the computer with a certain probability, and each person's preferences are independent, i.e., your favorite school does not change because of the others' favorites; the school chooses the student with the highest score. In each round of the school choice experiment, you make your choice of schools based on your preferences and in combination with others, filling in what you think is the best. At the end of each round, you will learn your admissions results, and students who drop out (i.e., are not admitted to the school of their choice) will be admitted to the school with the same payoff as the last-place school under that student's preference. There are twenty rounds of applications in total, each round being independent and having no effect on each other.

The next experimental process takes place in fixed groups of four, and there are 20 rounds, with your performance ranked in the third place in each round. Different rounds of the experiment are conducted independently, i.e., the payoffs in each round are independent. We will randomly select one of the 20 rounds of payoff as your gain in this task. At the same time, you can see the payoff you can get by being accepted to each school under your preference. In the experiment, you will know the probability (p) of which preference the student in the top two is. In this part of the experimental task, the first and second place students are served by a computer that will choose the top two schools under that preference in order according to the preference they are assigned (realized with probability p).

The decision you need to make in this experiment is to fill out the application based on your own ranking and preference, and the probability of other people's preferences. You can fill in two different first and second school choices at the same time, but the preference for the first choice is required to be higher than the second, i.e., in the case of school choice preference type 1 (see the table below), the first and second volunteers can be school A and school B, respectively; and cannot be school B and school A, respectively. The four schools choose the highest ranking among

candidates who declare the same volunteer, and do not consider that this is the candidate's first choice: The principle of parallel admission.

Four schools: School A, School B, School C and School D.

Admission rules: the principle of the Chinese parallel admission.

School Choice Preferences: There are two school choice preferences, as shown in the following table:

School choice preference Type 1	**School choice preference Type 2**
School A $>$ School B $>$ School C $>$ School D	School C $>$ School D $>$ School B $>$ School A

In each round of the experiment you will know the school choice preference you were assigned, but only the probability that the top two students are of which school choice preference. Your admission to the school ranked first in your school choice preference brings the highest benefit, the second school brings the next highest benefit, the third school brings the next highest benefit, and the fourth school (the guaranteed school) brings the last benefit. At the beginning of each round of decision making, the computer randomly assigns your preferences. In each of these 20 rounds of the experiment, your school choice preferences, gains, and the probability of other students' school choice preferences may be different. The acceptance results and gains for each round are revealed at the end of that round, so that you can know for each round whether you were accepted to the school you volunteered for and the corresponding gains. Again, it is important to emphasize that the only gains from the 20 rounds are the randomly selected rounds that are your gains from the experiment in this section. The exchange rate of experiment points to cash is 3:1. in addition you will receive a ¥10 show-up fee.

Admission mechanism details: Suppose Amy's school choice preference is preference 1 (school A $>$ school B $>$ school C $>$ school D), and also suppose she ranks first in a group of four. If she fills in the first preference for school A and the second preference for school B (hereinafter referred to as "school A and school B"), she will be admitted to school A with the gain of S(A); if she fills in school B and school C, she will be admitted to school B with the gain of S(B); if she fills in school C and school D, she will be admitted to school C with the gain of S(B); if she fills in school B and

school C, she will be admitted to school D with the gain of S(B). If she fills in school C and school D, she will be admitted to school C, and the gain is S(C), and so on.

The third-ranked Bob and the first-ranked Amy also have school choice preference 1 (school A > school B > school C > school D), and Amy chooses school A and school B, and Bob chooses school B and school C. At this time, for the second-ranked Carl, if he fills in school A and school B, he will be admitted by school B in the next place, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B); if he fills in school B and school C, he will still be admitted by school B, and the gain is S (B). B and gain S(B).

Next, to confirm that you understand our experiment description and rules, you will do a simple test that will not be correlated with the experiment gains, but simply to make sure that your reading comprehension of the game rules is not biased. All results in the experiment will be anonymous and we will keep your decisions in this task strictly confidential. If you have any questions, please raise your hand to one of our experiment assistants and they will answer your questions as soon as possible. Please have a calculator ready if needed.

Now for round 1/20 application:

You are school preference type 1 in this round of the school choice experiment.

The admission gain for preference 1 is school A (300) > school B (20) > school C (15) > school D (0)

You are ranked third in a group of four (with the computer in fourth place).

There is a 75% probability that the top two ranked students have preference 1.

Please choose two schools as your choice of volunteer (note: two options can not be repeated), four schools will follow the principle of parallel volunteering to choose the highest score, your admission results will determine the benefits of your experiment in this round.

Based on the probability of other ranked students' preference categories and their application strategies, the probability of admission corresponding to your choice is:

- First choice is A and the second choice is B, then the probability of admission to the first choice is: 6.25%; the probability of admission to the second choice is: 40.0%;
- If the first choice is A and the second choice is C, the probability of admission to the first choice

is: 6.25%; the probability of admission to the second choice is: 60.0%;

- If the first choice is A and the second choice is D, the probability of admission to the first choice is: 6.25%; the probability of admission to the second choice is: 100.0%;

- If the first choice is B and the second choice is C, the probability of admission to the first choice is 44.0%; the probability of admission to the second choice is 100.0%;

- If the first choice is B and the second choice is D, the probability of admission to the first choice is 44.0%; the probability of admission to the second choice is 100.0%;

- If the first choice is C and the second choice is D, the probability of admission to the first choice is 56.0% and the probability of admission to the second choice is 82.0%.

Your first choice is

A. School A

B. School B

C. School C

D. School D

Your second choice is

A. School A

B. School B

C. School C

D. School D

Contingent Thinking Questions

Scenario 1

There are two cards, one is black on both sides and the other is black on one side and white on the other. We take any one of these two cards, and then we make the selected card face up on either side. You can see the face-up side of the card on your screen, and the color of the face-up card is black. Please give the probability that you think the back side of the card is black. You can enter a number from 0 to 100 in the space below to represent the percentage probability you think, then click "OK". For example, the number 40 means that you think the odds of the back side of the card being black are 40%, or 0.4; the number 60 means that you think the odds of the back side of the card being black are 60%, or 0.6, and so on.

Your gain in this task depends on the amount of difference between your answer and the correct answer. If your answer is exactly the correct answer or deviates by less than 1 percentage point, you will receive a cash reward of ¥1. If your answer deviates by between 1 and 5 percentage points, you will receive a cash reward of ¥0.50; for all other answers, you will only receive ¥0.

The probability that the color of this side of the card with the back side down is black is _________ (0-100, can be accurate to two decimal places) %. [Correct Answer: 66.67]

Scenario 2

Similarly, there are two cards, one is black on both sides and the other is black on one side and white on the other. We draw any one of these two cards, and then arbitrarily leave one side of the selected card face up. Suppose a calculating player cannot currently see the face-up card, but must guess whether the back-side down card is black or white, and if her guess is correct she wins a prize of 60 RMB. Now our question is how much do you think this savvy player would be willing to pay to learn the color of the face-up card. Please give us what you think the player thinks the value of the information about the color of the face-up card is (in RMB) by putting a number from 0 to 60 in the space below to represent the value you think it is and then clicking "OK".

Your profit in this task depends on the amount of difference between your answer and the correct answer. If your answer is exactly the correct answer or is less than 1 percentage point off, you will receive a ¥1 cash prize; if your answer is between 1 and 5 percentage points off, you will receive a

¥0.50 cash prize; for all other answers, you will only receive ¥0.

You think this player thinks the value of the information about the color of the face-up card is ________ (0 - 60) dollars.

[Correct Answer: 0]

Scenario 3

There are three cards, one that is black on both sides, another that is black on one side and white on the other, and another that is white on both sides. Let's take any one of these three cards, and then let any one of the selected cards face up. You can see the face-up side of the card on your screen, and the color of the face-up card is black. Please give the probability that you think the back side of the card is black. You can enter a number from 0 to 100 in the space below to represent the percentage probability you think, then click "OK". For example, the number 40 means that you think the odds of the back side of the card being black are 40%, or 0.4; the number 60 means that you think the odds of the back side of the card being black are 60%, or 0.6, and so on.

Your gain in this task depends on the amount of difference between your answer and the correct answer. If your answer is exactly the correct answer or deviates by less than 1 percentage point, you will receive a cash reward of ¥1. If your answer deviates by between 1 and 5 percentage points, you will receive a cash reward of ¥0.50; for all other answers, you will only receive ¥0.

The probability that the color of this side of the card with the back side down is black is ________ (0-100, can be accurate to two decimal places) %. [Correct Answer: 66.67]

Scenario 4

Again, there are three cards, one is black on both sides, another is black on one side and white on the other, and one is white on both sides. We draw any one of these three cards and then arbitrarily make this selected card face up on one of its sides. Suppose a calculating player cannot see the face-up card at the moment, but must guess whether the back-side down card is black or white, and if her guess is correct she will be rewarded 60 RMB. Now our question is how much do you think this savvy player would be willing to pay to learn the color of the face-up card. Please give us what you think the player thinks the value of the information about the color of the face-up card is (in RMB) by putting a number from 0 to 60 in the space below to represent the value you think it is and then clicking "OK".

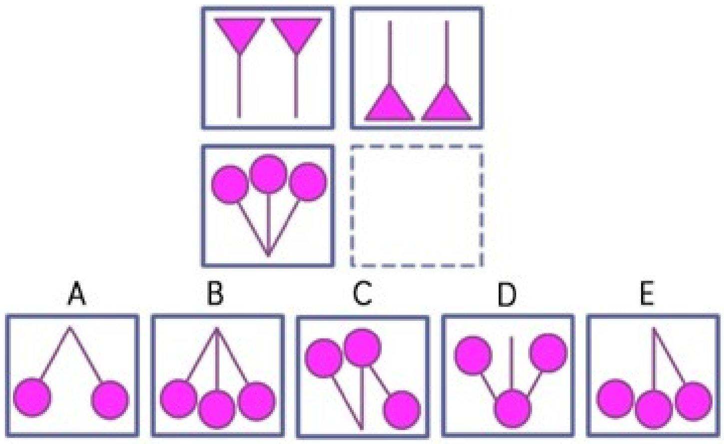
Your profit in this task depends on the amount of difference between your answer and the correct answer. If your answer is exactly the correct answer or is less than 1 percentage point off, you will receive a ¥1 cash reward; if your answer is between 1 and 5 percentage points off, you will receive a ¥0.50 cash reward; for all other answers, you will only receive ¥0.

Do you think this player thinks the value of the information about the color of the face-up card is _________ (0 - 60) yuan.

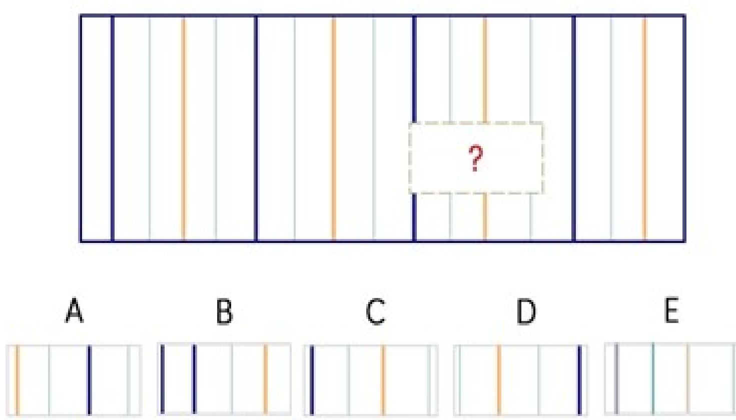
[Correct answer: 10].

Raven's Advanced Progressive Matrices-IQ test

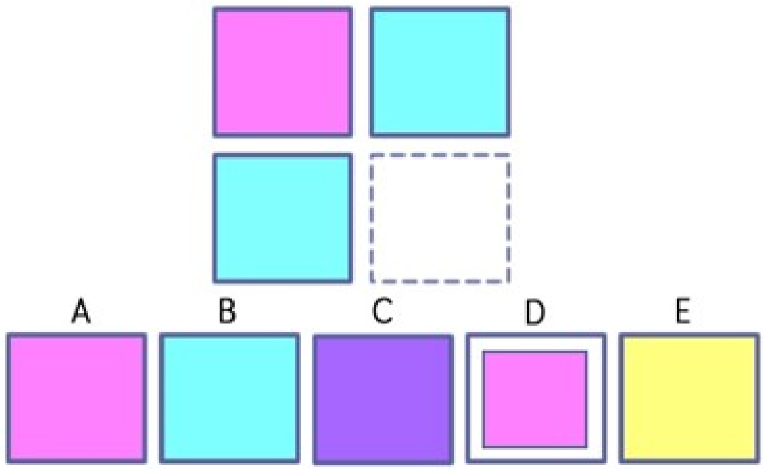
(1) Observe the two small boxes at the top. Can you see how the shapes in the two small boxes are related? Then, according to this relationship, can you find the shape of the figure in the small box in the lower right dashed line?



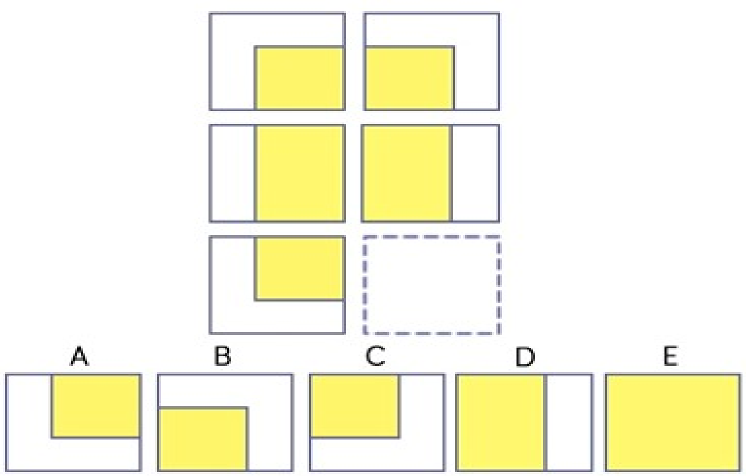
(2) Please look at the figure below, there is a small piece of the figure missing, can you find it?



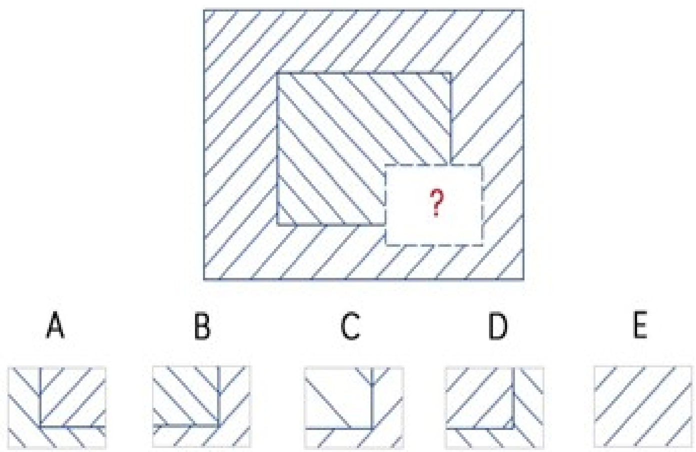
(3) Please observe the two small boxes at the top, can you see what consistent features they have? Next, please look at the two small boxes at the bottom. When the dotted line in the lower right corner looks like what, the small box below and the small box above can show similar characteristics?



(4) Look at the two small boxes in the first row. Can you see how they are related? Can you find the graph inside the dotted line according to this rule?



(5) Look at the graph below. One piece of the graph is missing.



(Solutions: B, C, A, C, B)

Risk Attitude Task

At the bottom of this page, you will see a table with 10 rows, each row corresponding to a question numbered from 1 to 10. each question has Choice A and Choice B. Choice A and Choice B offer different chances to win.

The computer draws a random number between 1 and 10. The question corresponding to the number is used to determine your final earnings.

Your final payout is determined by the computer's roll of a virtual 10-sided die and your choice (A or B) for that question. each number from 1 to 10 has the same probability of appearing.

You don't need to choose A or B for every question; you just need to tell us where you would like to start with B (instead of A).

Do you have any questions about the above rules of the game?

Table A.1: Risk attitude table

Scenario	Option A	Choice	Option B	Choice
1	Dice number 1 (¥10) Dice number 2-10 (¥8)		Dice number 1 (¥19.25) Dice number 2-10 (¥0.5)	
2	Number 1-2 (¥10) Number 3-10 (¥8)		Number 1-2 (¥19.25) Number 3-10 (¥0.5)	
3	Number 1-3 (¥10) Number 4-10 (¥8)		Number 1-3 (¥19.25) Number 4-10 (¥0.5)	
4	Number 1-4 (¥10) Number 5-10 (¥8)		Number 1-4 (¥19.25) Number 5-10 (¥0.5)	
5	Number 1-5 (¥10) Number 6-10 (¥8)		Number 1-5 (¥19.25) Number 6-10 (¥0.5)	
6	Number 1-6 (¥10) Number 7-10 (¥8)		Number 1-6 (¥19.25) Number 7-10 (¥0.5)	
7	Number 1-7 (¥10) Number 8-10 (¥8)		Number 1-7 (¥19.25) Number 8-10 (¥0.5)	
8	Number 1-8 (¥10) Number 9-10 (¥8)		Number 1-8 (¥19.25) Number 9-10 (¥0.5)	
9	Number 1-9 (¥10) Dice number 10 (¥8)		Number 1-9 (¥19.25) Dice number 10 (¥0.5)	
10	Dice number 10 (¥10)		Dice number 1-10 (¥19.25)	

From which point on, you switch from Option A to Option B?

Ambiguity Aversion Task

Now there are two opaque jars C and D. Each jar contains 100 red or black balls. The 50 balls in jar C are red and the other 50 are black; while the 100 balls in jar D are also red and black, but exactly how many balls are red or how many balls are black is unknown.

First, you will choose a color, red or black, as your lucky color. Next, you will randomly choose one of the two jars and draw a small ball, if you draw the small ball and your lucky color, then you will get the corresponding reward; if you draw the small ball and your selected lucky color is not the same, then you will not get this part of the reward.

Similar to task 1, on the screen we will give the color composition of the balls in jar C and jar D for different scenarios, specifically, there are 20 scenarios in total. In each scenario, you pick whether to choose jar C or jar D based on the lucky color you choose.

At the end of the experiment, we will be similar to Task 1, first a scenario will be randomly selected, then a small ball will be randomly selected in that jar you chose, and if the color of the small ball is the same as the lucky color you chose, then you will be rewarded accordingly. The amount of reward is different under each scenario. The specific details of the reward will be detailed in the next part, please read carefully.

First, please choose your lucky color:

1) Red

2) Black

Please remember your lucky color. Next, you will make the decision to choose the jar in 20 consecutive scenarios, if the color of the ball in the last randomly selected scenario matches your lucky color, then you will get the corresponding reward, the reward under each scenario is different, please read carefully.

From which scenario on, you switch from Jar C to Jar D?

Table A.2: Ambiguity aversion table

Scenario	Jar C (50 red balls, 50 black balls)	Choose C	Choose D	Jar D (100 balls, ? red balls, ? black balls)
1	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥8.2 Not selected ¥0
2	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥8.6 Not selected ¥0
3	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥9 Not selected ¥0
4	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥9.4 Not selected ¥0
5	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥9.8 Not selected ¥0
6	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥10.2 Not selected ¥0
7	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥10.6 Not selected ¥0
8	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥11 Not selected ¥0
9	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥11.4 Not selected ¥0
10	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥11.8 Not selected ¥0
11	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥12.2 Not selected ¥0
12	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥12.6 Not selected ¥0
13	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥13 Not selected ¥0
14	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥13.4 Not selected ¥0
15	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥13.8 Not selected ¥0
16	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥14.2 Not selected ¥0
17	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥14.6 Not selected ¥0
18	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥15 Not selected ¥0
19	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥15.4 Not selected ¥0
20	Pick lucky color ¥10 Not selected ¥0			Pick lucky color ¥15.8 Not selected ¥0

Exit Survey

1. Your gender is

A. male

B. Female

2. Your age is ____ (number, integers between 10-99)

3. Your family hukou type is

A. Urban *hukou*

B. Rural *hukou*

C. Other

4. Your grade level is

A. Freshman

B. Sophomore

C. Junior

D. Senior

E. Master's degree

F. Doctor

G. Other

5. You took the entrance exam in year ____? (Programming upper and lower limits: numbers, integers between 2000 and 2022)

6. What was your score in the college entrance examination? ____ (Programming upper and lower limits: numbers, integers between 100 and 1000)

7. In which province or city did you take the college entrance exam? ____ province ____ city

8. Do you think the guidebook or similar materials for the college entrance examination are helpful in filling out the college entrance examination, ranked from 0 (not useful) to 5 (very useful), and to what extent did the guidebook help you to fill out the college entrance examination? (Programming: 6 options and no materials provided, total of 7 options, single choice)

9. Which place (first, second, or third) did you rank your current university when you applied to colleges?

10. Can you attend a better university than your current university with your score (if you do not consider your major)? (Yes/No/Unsure, single choice)

11. If your province has adopted parallel admission rule, please answer: Do you think you were not able to attend a better university because you were too conservative in your first and second choices? (Yes/No/Don't know/Non-parallel admission, single choice)

12. If your province adopted parallel admission rule, please answer: Do you think you did not get into a better university because you were too aggressive in the first few applications? (Yes/No/Unsure/Non-parallel admission, single choice)

Do you agree that there should be a certain gradient in applications? (Yes/No/Don't know, single choice)

14. Do you think being rejected by the first choice will affect your choice of the second volunteer? (Yes/No/Don't know, single choice)

15. If you were to use the one-by-one method of applications, that is, after filling out the first choice and learning that you were not accepted then filling out the second choice and so on until you were accepted to a particular school, do you think this method would get you into the right school better than parallel admission rule? (Yes/No/Unsure, single choice)