DEPARTMENT OF INTERNATIONAL AND EUROPEAN ECONOMIC STUDIES

ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

Comparative Ignorance as an Explanation of Ambiguity Aversion and Ellsberg Choices: A Survey with a New Proposal for Bayesian Training

Phoebe Koundouri

Nikitas Pittis

Panagiotis Samartzis

Konstantinos Georgalos

Working Paper Series

25-72

December 2025

Comparative Ignorance as an Explanation of Ambiguity Aversion and Ellsberg Choices: A Survey with a New Proposal for Bayesian Training

Phoebe Koundouri* Nikitas Pittis† Panagiotis Samartzis‡
Konstantinos Georgalos§

December 14, 2025

Abstract

Ellsberg-type choices challenge the Bayesian theory of Subjective Expected Utility Maximization (SEUM) and reveal a key behavioural trait: Ambiguity Aversion (AA). Two main interpretations of AA exist. One treats AA as rational; the other sees it as a psychological bias. This paper adopts the latter view and focuses on the leading psychological account of AA, Fox and Tversky's (1995) Comparative Ignorance Hypothesis (CIH). CIH argues that AA arises as a "comparative effect" when a decision maker (DM) feels epistemically inferior for some events relative to others. In such cases, the DM becomes averse to betting on the epistemically weaker events.

*School of Economics and ReSEES Laboratory, Athens University of Economics and Business; Sustainable Development Unit, Athena Research Center; World Academy of Arts and Science; UN SDSN-Europe. ✉ pkoundouri@aueb.gr, phoebe.koundouri@icre8.eu (Corresponding author)

†Department of Banking and Financial Management, University of Piraeus, Greece. ✉ npittis@unipi.gr

‡Department of Economics, University of Macedonia. ✉ psamartzis@uom.edu.gr

§Department of Economics, Lancaster University Management School, LA1 4YX, Lancaster, U.K. ✉ k.georgalos@lancaster.ac.uk

Koundouri, Samartzis and Georgalos acknowledge funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 951424; ERC-SyG Water-Futures).

The paper has three goals. First, it surveys the literature on CIH. Second, it introduces a new "Bayesian Training" (BT) procedure grounded in counterfactual thinking. A DM who engages in BT may escape comparative ignorance, reduce AA, and align more closely with Bayesian behaviour. Finally, we present the results of an economic experiment where we aim to test the impact of Bayesian training on behaviour.

Keywords: counterfactual priors, ambiguity, Ellsberg paradox.
JEL Classification: C44, D81, D83, D89

1 Relevant Experimental Literature

The main objective of the experiment is to combine the experimental literature on ambiguity with the literature that evaluates the normative content of subjective expected utility and its axioms. The ambiguity literature provides robust tools for belief elicitation and ambiguity attitudes, while the normative SEU literature allows us to study whether (and how) Bayesian training affects subjects' choices.

Benjamin et al. (2021) classify four main approaches through which the experimental literature has attempted to measure normatively relevant preferences: (i) revisiting earlier choices, either by repeating the same choice across rounds (Hey 2001; van de Kuilen and Wakker 2006; van de Kuilen 2009; Nicholls et al. 2015; Birnbaum and Schmidt 2015), by allowing revision (Breig and Feldman 2024; Yu et al. 2021; Crosseto and Gaudeul 2023), or by offering training (Eli 2017; Wu et al. 2023; Kuzmics et al. 2020); (ii) asking subjects to provide reasons for their decisions (Miller and Fagley 1991; Sieck and Yates 1997); (iii) inviting subjects to revise their choices in light of an axiom (MacCrimmon 1968; Slovic and Tversky 1974; Moskowitz 1974; MacCrimmon and Larsson 1979; Eli 2017; Nielsen and Rehbeck 2022; Herweg et al. 2024); and (iv) presenting a choice under two frames (McNeil et al. 1988; Miller and Fagley 1991; Sieck and Yates 1997; Druckman 2001; Benjamin et al. 2021).

Early choice-revision studies (MacCrimmon, 1968; Moskowitz, 1974; Slovic and Tversky, 1974) confronted subjects with arguments about violated axioms. More recent work elicits preferences over axioms directly and then tests whether subjects revise inconsistent choices. Benjamin et al. (2021) and Nielsen and Rehbeck (2022) show that confronting people with their own inconsistencies induces substantial revisions. Herweg et al. (2024) examine whether violations of canonical axioms are mistakes or genuine preferences. Humphrey and Kruse (2024) replicate Slovic and Tversky (1974) with incentives and a larger sample, finding no systematic movement toward the sure-thing principle.

2 Experimental Design

The experiment consisted of two treatments, the Training and the Control treatment[1]. Each treatment had 3 parts followed by a short survey to collect written feedback and demographic information. Parts 1 and 3 were identical in both treatments where subjects faced the 3-colour, one-urn Ellsberg task before and after an intervention. The task involved draws from a virtual box filled with 9 balls, 3 of them known to be red and the remaining six divided between yellow and black in unknown proportions. Subjects faced two choice situations, Choice 1 and Choice 2, in which they were asked to choose between bets paying off £8 or £0, depending on the colour of the drawn ball. For instance, in Choice 1, a subject was asked to decide whether she prefers to bet on a red or on a black ball. Table 1 summarises the two relevant choice problems in the Ellsberg experiment.

		Red	Black	Yellow
Choice 1	f	£8	£0	£0
	g	£0	£8	£0
Choice 2	f^*	£8	£0	£8
	g^*	£0	£8	£8

Table 1: The 3-colour Ellsberg task

Assuming strict preferences, it is possible to classify subjects into ambiguity attitudes given their Ellsberg choices. Table 2 summarises this classification.

Subjects whose choices coincide with those in the first column (i.e. prefer a bet on a red ball to a bet on black ball, and also prefer a bet on a black or yellow ball to a bet on red or yellow ball) are classified as ambiguity averse. In other words, they show a

[1]The experimental design and the hypotheses have been pre-registered. The full pre-registered form is available here: https://osf.io/dmr5t/overview

	Averse	Neutral		Seeking
Choice 1	f	f	g	g
Choice 2	g^*	f^*	g^*	f^*

Table 2: Ambiguity attitudes in the Ellsberg's 3-colour experiment

strong preference to known probabilities. Conversely, subjects with choices as those in the last column, are classified as ambiguity seeking as they express preference towards events with unknown probabilities. The remaining two cases characterise ambiguity neutral subjects who appear to satisfy all Savage's axioms. A common issue with experiments studying ambiguity using bets on draws from the Ellsberg urn, is how to handle indifference between the available options within each choice.[2] To tackle this we ask subjects two complementary, non-incentivised questions that can function as a proxy for strict preference. In particular, we ask subjects, after their decision within each choice to express how confident they are about their choice (0 = not confident at all, 7 = very confident) and also to express how much they would be willing to accept to switch to the other option (£0 = I am relatively indifferent; £8 = I strongly prefer my choice). This practice has been widely used when preferences are imposed to be strict (see for example Chen et al. 2007; Dominiak et al. 2012 or Curley et al. 1989 who show that confidence is the best way to elicit a subject's ambiguity attitude in decision making among three different methods). The subjects repeated the task in part 3. In both parts the task was monetarily incentivised[3].

The second part of the experiment consisted of the training phase (intervention) which differed between the Training and the Control treatments.

2.1 Training Treatment

Our Training treatment is based on the idea that subjects may exhibit behaviour inconsistent with Expected Utility because they have difficulties assigning probabilities to events linked to balls drawn from an unknown distribution. This can be because sub-

[2]Allowing for a "I am indifferent between the two bets" option generates a new set of issues, such as how to implement this indifference which ultimately transforms the task. On the other hand, alternative methods to measure ambiguity attitudes would either require additional structural modelling assumptions or introducing a payoff asymmetry between the available options which could increase cognitive load and complexity perception.

[3]The subjects knew that one of the incentivised tasks would be chosen at random to be played out for real, but did not know that there would be a repetition of a task, or what the other tasks involved.

jects are genuinely averse to ambiguity, or because subjects have difficulties engaging in contingent reasoning, and therefore to counterfactual thinking[4]. The objective of the intervention is primarily to "nudge" subjects to think in a counterfactual way, rather than to rigorously train them to probability theory or to expose them to the normative appeal of the underlying axioms as the earlier literature did[5]. To do so, we asked subjects to respond to the following five questions/tasks:

Q_1-the first question of the training replicated the first part of the Monty Hall problem. In particular the subject faced the following question:

> Imagine you are a contestant on a game show. You are presented with three closed doors. Behind one of the doors is a car, and behind the other two doors, there is nothing. You must choose one door. Before you make any further decisions: What is the probability that the car is behind Door 1, Door 2, or Door 3?

Purpose of this question was to help us screen subjects who may have difficulties understanding objective probabilities. Subjects could choose a probability for each door from a drop-down menu with available options of 0%, 50%, 33.3%, 100% and "cannot be determined". If the sum of the probabilities did not sum to 100% the software was programmed to remind subjects of this rule. Similarly, if a subject would select anything different from 1/3 chances for each door, the software would ask them whether they agree with the following statement 'the probability is equal to 1/3 for each door.'

Q_2-in this task, subjects were presented with a pair of binary lotteries with two possible outcomes, each with an associated probability to help us understand whether subjects were using expectation based approaches (i.e. expected value, expected utility) to evaluate lotteries, or they would resort to heuristic decision making (e.g. maxmin). The lotteries were presented on the screen side by side, in the form of pie charts to represent the corresponding probabilities. First they were asked to choose a lottery. Then, they had to indicate the reasons for their choice from a menu of four available options (the could select up to 2 options). The menu included the following options:

[4]Recent experiments with a focus on contingent reasoning, uncertainty and failures in forming beliefs, see Martínez-Marquina et al. 2019; Enke 2020; Esponda and Vespa 2023 among others, and Esponda and Vespa 2024 for a review.

[5]See for example MacCrimmon 1968; Slovic and Tversky 1974; Moskowitz 1974; MacCrimmon and Larsson 1979 or more recently Humphrey and Kruse 2024.

- how likely the outcomes are to occur
- how much I value the monetary outcomes
- how familiar or comfortable the option feels to me
- how risky the option feels regardless of actual probabilities

If a subject would select anything different to both the first two options, the software would then ask them to provide in a free text box the reasons why they did not select one or both of the two first reasons.

Q_3- was inspired by the design of Chew et al. (2018) and was asking subjects to quantify the probability of drawing a black ball from the box, given that it is known that there are already 3 red balls in the box. The four available options included more, less or equal to 1/3 (33.3%) and "cannot be determined". Acceptable responses are 1/3 and "cannot be determined". This question allows us to classify subjects as probability-minded and ambiguity-minded. If a different response was given, the software would ask participants to provide their reasoning in a free-text box.

Q_4- reminded subjects that there are 1/3 objective chances of a red ball to be drawn from the box, while one may believe that there are also 1/3 chances for a black ball to be drawn. The subjects were then asked whether they agree that the probability of a red ball is more "reliable" and that the probability of black felt less sure (principle of comparative ignorance).

Q_5- applied the *probability matching* method (Dimmock et al., 2016; Baillon et al., 2018) to elicit the subjective probability that subjects attach to the event of a black ball. For an event E, the method elicits the simple, objective probability that makes the subject indifferent between betting on the event E and betting on a simple lottery that gives the prize with that probability. As stimuli, we used choice lists where subjects were asked to choose between two options: win £8 if a black ball is drawn or win £8 with p% probability and nothing otherwise. The objective of this question was to address the main cause of the Comparative Ignorance Hypothesis, that a subject feels "epistemically inferior" when facing an ambiguous event compared to a known risk. The probability matching task could contribute to eliminate this feeling of inferiority by making the decision-maker (DM) realise that, under the principle of insufficient reason (symmetry), the ambiguous event can be assigned a probability (e.g., 1/3). The probability matching method is an ideal tool to operationalise this training because it forces the DM to perform the crucial cognitive step required for Bayesian decision-making: assigning an explicit, numerical probability to an ambiguous event. This task was incentivised.

2.2 Control Treatment

In the Control treatment, subjects completed a tutorial on how to solve Raven's Progressive Matrices. The choice of this task, as well as the number of questions included, was motivated by three considerations. First, we sought a task that did not involve probability calculations or items with intuitively appealing but incorrect answers that require reflective thinking (e.g., the Cognitive Reflection Test). Second, we aimed to ensure that the duration of the task closely matched the time required for the Bayesian training. Finally, we selected a task whose difficulty level—and associated cognitive effort—would be comparable to that demanded by the Bayesian training. The experimental design is summarised in Table 3.

Timeline	Control	Training Treatment
	Instructions	Instructions
Part 1	Ellsberg 3-colour task	Ellsberg 3-colour task
Part 2	Training on Raven's matrices	Bayesian Training
Part 3	Ellsberg 3-colour task	Ellsberg 3-colour task
	Demographics	Demographics

Table 3: Experiment timeline.

2.3 Hypotheses

Based on our theoretical framework and experimental design, there are three main hypotheses that we aim to explore:

Hypothesis 1 *Reduction of Ambiguity Aversion through Bayesian Training*

Participants in the Training treatment are expected to show a lower rate of ambiguity-averse choices in Ellsberg-style problems after undergoing a Bayesian Training (BT) procedure, compared to their initial responses. On the contrary, no effect is expected in the control group where subjects participate in an equally cognitively challenging task but without any focus on probabilities.

Hypothesis 2 *The Bayesian training will be more effective for subjects classified as "ambiguity-minded" compared to those classified as "probability-minded".*

Given that those subjects classified as probability minded are already thinking along the lines of insufficient reason, the Bayesian training is not expected to have any effect on them.

Finally, given the complexity involved in understanding and calculating probabilities, we expect that the Bayesian training will be more effective for subjects coming from quantitative studies background.

Hypothesis 3 *The Bayesian training will be more effective for subjects studying quantitative oriented degrees.*

A total of 139 subjects (51.1% female) were recruited using ORSEE (Greiner, 2015) from a pool of volunteers at the Lancaster Experimental Economic Lab (LExEL) at Lancaster University. Participants were randomly allocated to one of the two treatments (Training or Control) and each subject was allowed to participate only once. The experimental interface was custom-developed in Python and was implemented via Streamlit. The average payment was £9 (including a show-up fee of £5) and sessions lasted for up to 30 minutes. Payments were made immediately after the experiment via bank transfer.

3 Results

In what follows, we first report the results from parts 1 and 2, followed by some analysis of the data from the training session. Table 4 reports the classification of subjects according to their ambiguity attitude—ambiguity averse, neutral, or seeking—for both treatments and both stages (pre- and post-intervention). The last column presents p-values from one-tailed chi-square tests of equality of proportions.[6]

[6]We use one-tailed tests as our hypotheses predict a clear directional effect, namely that Bayesian training should reduce the proportion of non-neutral ambiguity attitudes.

		Training		Control		diff
		#subjects	%	#subjects	%	p-value
Pre-intervention	AA	27	0.397	36	0.507	0.096
	AN	30	0.441	25	0.352	0.142
	AS	11	0.162	10	0.141	0.635
Post-intervention	AA	25	0.368	37	0.521	0.034
	AN	35	0.515	25	0.352	0.027
	AS	8	0.118	9	0.127	0.435

Table 4: Classification of subjects into ambiguity attitudes—ambiguity averse (AA), ambiguity neutral (AN), and ambiguity seeking (AS)—for both treatments (Training and Control) and both stages (pre- and post-intervention). The last column reports p-values from one-tailed chi-square tests of equality of proportions.

Across treatments, the overall distribution of attitudes is broadly comparable, with most subjects classified as ambiguity averse or neutral, and only a small minority as ambiguity seeking. At baseline (part 1), 39.7% (50.7%) of subjects in the Training (Control) group are ambiguity averse, 44.1% (35.2%) are ambiguity neutral, and 16.2% (14.1%) are ambiguity seeking. None of these differences are statistically significant. Overall, the pre-intervention distributions are consistent with those typically observed in similar Ellsberg-style experiments.

After the intervention (part 3), the distribution of ambiguity attitudes differs more visibly between the two treatments. In the Training group, 36.8% of subjects are classified as ambiguity averse, compared to 52.1% in the Control group, a difference that is statistically significant at the 5% level ($p = 0.034$). Ambiguity neutrality is correspondingly more common in the Training group (51.5%) than in the Control group (35.2%), and this difference is also statistically significant ($p = 0.027$). In contrast, the proportion of ambiguity-seeking subjects remains very similar across treatments (11.8% vs. 12.7%, $p = 0.435$). Overall, the post-intervention data indicate that subjects in the Training group are more likely to display ambiguity-neutral attitudes and less likely to be ambiguity averse relative to the Control group, providing supporting evidence for Hypothesis 1.

Table 5 reports the within-subjects, between-parts changes in ambiguity attitudes by means of a contingency matrix. In particular, it reports aggregate behaviour in pre-intervention (part 1) and post-intervention (part 3) choices along with the transition of types between parts, for both treatments. The rows correspond to the classification of types pre-intervention, therefore, the sum of a row indicates the number of subjects classifies as that type. For instance, in the left panel, the first row shows 27 subjects (16+11) are classified as ambiguity averse in part 1, while out of these 27 subjects, 11 changed to ambiguity neutral in part 3. Similarly, the sum in a column shows the number of subjects of a particular attitude in part 3.

		Training					Control		
		Part 3					Part 3		
		AA	AN	AS			AA	AN	AS
Part 1	AA	16	11	0	Part 1	AA	30	6	0
	AN	7	20	3		AN	7	15	3
	AS	2	4	5		AS	0	4	6

Table 5: The table reports the contingency matrix showing how subjects transitioned to different ambiguity attitudes between parts, for the two treatments. The rows report the classification in part 1 (pre-intervention) and the columns in part 3 (post-intervention).

To assess whether the intervention induced a systematic structural change in attitude dynamics, we used a Log-Linear Model Comparison to test the three-way interaction (Pre-Attitude × Post-Attitude × Treatment). This test, which compares the overall pattern of attitude transitions across all nine cells of the 3×3 matrix, yielded a non-significant result ($G^2 \approx 3.899$, $p \approx 0.419$). This provides evidence that the Training did not induce a broad, widespread, systemic restructuring of the underlying ambiguity attitude dynamics. However, to evaluate our primary research hypothesis—the specific increase in ambiguity neutrality—a Targeted One-Sided Test of Proportions was employed. This test found the final proportion of Ambiguity Neutral subjects to be statistically significantly higher in the Training group than in the Control group ($\chi^2 \approx 3.745$, $p \approx 0.0264$). This pattern suggests that the observed transition to neutrality can be attributed to the effective influence of the Bayesian training, rather than a non-specific or random effect.

We now report some aggregate results from the Bayesian Training tasks, followed by some regression analysis.

In Q_1, the Monty Hall question 66/68 (97%) of the subjects selected the correct answer confirming that subjects in our sample did not have difficulty attributing objective probabilities to events.

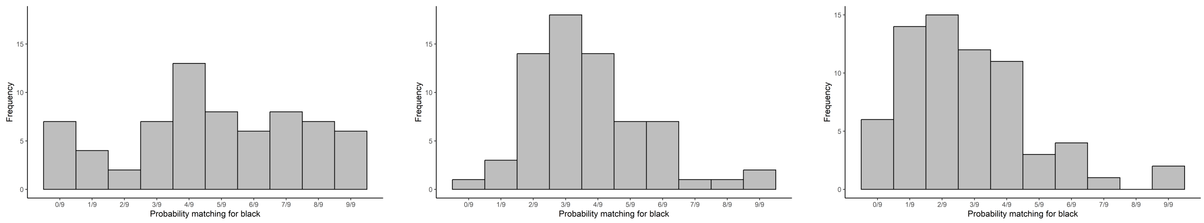
In Q_2, the lottery task, 25/68 (36.8%) chose the two first options (how likely the outcomes are to occur, and how much I value the monetary outcomes). Analysing the free text responses that subjects provided, some appear to have resorted to heuristic decision making, while others to maxmin reasoning.

In Q_3, 16 out of 68 (23.5%) subjects were classified as probability-minded and 32 out of 68 subjects (47.1%) were classified as ambiguity-minded.

In Q_4, 62 out of 68 subjects (91.2%) replied "Yes, probably yes" to the question of whether they feel the probability of red to be more reliable compared to that of black, a statement that is largely in line with the Comparative Ignorance Hypothesis.

Finally, in Q_5, the structure of the multiple price list task allows the available options to serve as a critical rationality and consistency screen. For instance, a subject consistently choosing the ambiguous option (A, a bet on a black ball with $P(win) < 1.0$) over the sure payoff in the final row violates the principle of Stochastic Dominance. This behaviour cannot be accounted for by any ambiguity attitude (non-neutral or otherwise) and suggests a fundamental failure in comprehension of the incentive mechanism. Similarly, the physical structure of the urn imposes objective probability bounds on the events. For instance, When the urn contains 3 red balls, the maximum possible probability of drawing a black ball is 6/9. A subject whose switching point implies a matching probability $m(black)$ greater than 8/9 (i.e., choosing A at the second-to-last row) is exhibiting behaviour that is inconsistent with the objective constraints of the problem and one needs to make extreme assumptions of ambiguity-seeking preferences to rationalise such choices. In our data, only 1 subject chose always A in all 3 scenarios, while overall, less than 5% of all choices indicated a uniform preference for A. We use the switch point as the indifference point (matching probability). Figure 1 shows the histograms of the elicited probability-matching responses across the three scenarios: a box containing 1 red ball (left panel), 3 red balls (middle), and 5 red balls (right). The corresponding Bayesian probabilities of drawing black (and, by symmetry, yellow) in these scenarios are 4/9, 3/9 and 2/9 respectively. The plots suggest that, in all three cases, the mode of the reported probabilities aligns with the Bayesian benchmark.

Dimmock et al. (2016) extend the definitions of Abdellaoui et al. (2011) and pro-



(a) $P(R) = 1/9$ (b) $P(R) = 3/9$ (c) $P(R) = 5/9$

Figure 1: The figure presents histograms of participants' probability-matching choices for black under three conditions: boxes containing 1 red ball (left panel), 3 red balls (middle panel), and 5 red balls (right panel). The Bayesian probabilities of drawing black in these conditions are 4/9, 3/9 and 2/9 respectively.

vide the decision-theoretic foundation for matching probabilities. Let the prospect $\alpha_E\beta$ which yields outcome α if event E occurs, otherwise yields outcome β. For a risky event with objective probability p the prospect can be written as $\alpha_p\beta$. The matching probability $P(E) = p$ is formally defined by $\alpha_p\beta \sim \alpha_E\beta$. Defining $P(E)$ the ambiguity-neutral (a-neutral) probability of event E the subjective probability used by an ambiguity neutral decision maker then p is the matching probability such that $m(P(E)) = p$.

$$AA_1 = \frac{4}{9} - m_1(black)$$

$$AA_3 = \frac{3}{9} - m_3(black)$$

$$AA_5 = \frac{2}{9} - m_5(black)$$

The ambiguity attitude of each subject was decomposed into two independent dimensions—Ambiguity Aversion (β_{So}) and A-Insensitivity (α_{So})—following the methodology established by Dimmock et al. (2016). This decomposition requires estimating the linear relationship between the elicited matching probability (m) and the corresponding a-neutral probability (p). Specifically, for each individual, the three data points (pre-intervention or post-intervention) were used to estimate the parameters ($\hat{\alpha}$, $\hat{\beta}$) of the following function via Ordinary Least Squares (OLS) regression:

$$m(p) = \hat{\alpha} + \hat{\beta}p + \epsilon$$

The fitted parameters ($\hat{\alpha}$ and $\hat{\beta}$) are then used to define the core indices. The A-Insensitivity Index, which captures the degree to which a subject is insensitive to changes in p, is derived from the slope as $a_{So} = 1 - \hat{\beta}$. The Ambiguity Aversion Index, representing the average vertical shift from neutrality, is calculated as the average premium: $\beta_{So} = \frac{1}{3}\sum_{i=1}^{3}(p_i - m_i)$. [I AM NOT SURE IF WE ARE GOING ANYWHERE WITH THIS ANALYSIS. I am trying to see if there is a way to discuss correlation/causality between this part and parts 1 and 3, but without much success]

Finally, to test our two remaining hypotheses, we run a series of regressions. In particular we are interested in testing the impact of a number of factors on behaving in an ambiguity neutral way in part 3. Therefore, we use the binary variable of whether the subject made the ambiguity neutral choice in part 3 as the dependent variable. As we are interested in the subjects that initially made an ambiguity non-neutral choice the regressions use only that subsample. Table 6 reports the average marginal effects (AMEs) from four probit specifications estimated on the sample of participants who were either ambiguity averse or ambiguity seeking at Stage 1. Each column corresponds to a different model including alternative sets of covariates. Out of a number of regressors, including demographics, confidence levels, willingness to accept, whether the subject specialises in a quantitative subject, or whether the subject is probability or ambiguity oriented, only the treatment variable was statistically significant in one model (at the 5% level) and marginally statistically significant (at the 10% level) in the others. In model 4, coefficient of the expressed confidence in part 3 is negative and significant (-2.220) indicating that a higher level of confidence leads to a lower probability of that subject to adopt the ambiguity neutral choice. The regressions, while they provide support in favor of hypothesis 1 and the impact of Bayesian training on ambiguity attitudes, they do not provide support to either of the two remaining hypotheses which state that Bayesian learning will have a larger impact on quantitative and ambiguity-oriented subjects.

	(1)	(2)	(3)	(4)
Treat	0.171^{**}	0.171^{*}	0.153^{*}	0.148^{*}
	(0.099)	(0.093)	(0.094)	(0.090)
Female	0.087	0.088	0.103	0.106
	(0.099)	(0.101)	(0.102)	(0.098)
Age	-0.008	-0.006	-0.002	-0.005
	(0.013)	(0.013)	(0.134)	(0.013)
Wta1	-0.077	-0.160	-0.153	-0.080
	(0.142)	(0.105)	(0.104)	(0.142)
Wta3	-0.124		-0.026	-0.011
	(0.139)		(0.107)	(0.130)
Confidence1	0.102	-0.014		0.102
	(0.130)	(0.107)		(0.127)
Confidence3	-0.192			-0.220^{*}
	(0.119)			(0.118)
Quantitative			0.117	0.143
			(0.094)	(0.097)
Log-likelihood	-46.403	-48.275	-47.620	-45.397
Pseudo-R^2	0.092	0.056	0.070	0.112
N	85	85	85	85

Table 6: The table reports average marginal effects (AMEs) from four probit specifications estimated on the sample of participants who were either ambiguity averse or ambiguity seeking at Stage 1. Each column corresponds to a different model including alternative sets of covariates. Standard errors are shown in parentheses. Significance levels: $p < 0.10$ (*), $p < 0.05$ (**), $p < 0.01$ (***). Log-likelihood and McFadden's pseudo-R^2 for each model are reported at the bottom of the table

As Humphrey and Kruse (2024) mention, experiments that allow subjects to revise earlier decisions may be susceptible to experimenter demand effects. In our experiment, to mitigate as much as possible such effects, we adopted two measures. First, we incentivised both decisions, assuming that incentives to reveal true preferences, along with anonymity are able to control for demand effects. Secondly, the intervention took place in such a way that it was not obvious that the repetition of the Ellsberg question is directly linked to it. Two reasons provide reassurance that demand effects do not lead our results. First, if subjects were responding to the training as intended, then we would not expect to see their decisions deviating toward ambiguity seeking or averse behaviour, but we would expect a higher concentration towards ambiguity neutrality. Then, there were many comments in the free text box, mentioning they thought there was a bug in the software, showing the same question twice, which provides evidence that subjects thought it was an accidental duplicate, not a deliberate pre/post measure, and therefore perhaps as a chance to revise earlier decisions.

References

Abdellaoui, M., Baillon, A., Placido, L., and Wakker, P. P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, 101(2):695–723.

Baillon, A., Huang, Z., Selim, A., and Wakker, P. P. (2018). Measuring ambiguity attitudes for all (natural) events. *Econometrica*, 86(5):1839–1858.

Benjamin, D. J., Fontana, M. A., and Kimball, M. S. (2021). Reconsidering risk aversion. Working Paper 28007, National Bureau of Economic Research.

Birnbaum, M. H. and Schmidt, U. (2015). The impact of learning by thought on violations of independence and coalescing. *Decision Analysis*, 12(3):144–152.

Breig, Z. and Feldman, P. (2024). Revealing risky mistakes through revisions. *Journal of Risk and Uncertainty*, 68(3):227–254.

Chen, Y., Katušcák, P., and Ozdenoren, E. (2007). Sealed bid auctions with ambiguity: Theory and experiments. *Journal of Economic Theory*, 136(1):513–535.

Chew, S. H., Ratchford, M., and Sagi, J. S. (2018). You need to recognise ambiguity to avoid it. *The Economic Journal*, 128(614):2480–2506.

Crosseto, P. and Gaudeul, A. (2023). Fast then slow: Choice revisions drive a decline in the attraction effect. *Management Science*.

Curley, S. P., Young, M. J., and Yates, J. F. (1989). Characterizing physicians' perceptions of ambiguity. *Medical Decision Making*, 9(2):116–124.

Dimmock, S. G., Kouwenberg, R., and Wakker, P. P. (2016). Ambiguity attitudes in a large representative sample. *Management Science*, 62(5):1363–1380.

Dominiak, A., Duersch, P., and Lefort, J.-P. (2012). A dynamic ellsberg urn experiment. *Games and Economic Behavior*, 75(2):625–638.

Druckman, J. N. (2001). Evaluating framing effects. *Journal of Economic Psychology*, 22(1):91–101.

Eli, V. (2017). *Essays in Normative and Descriptive Decision Theory*. PhD thesis, Paris-Saclay and HEC Paris.

Enke, B. (2020). What you see is all there is. *The Quarterly Journal of Economics*, 135(3):1363–1398.

Esponda, I. and Vespa, E. (2023). Contingent thinking and the sure-thing principle: Revisiting classic anomalies in the laboratory. *Review of Economic Studies*.

Esponda, I. and Vespa, E. (2024). Contingent thinking and the sure-thing principle: Revisiting classic anomalies in the laboratory. *The Review of Economic Studies*, 91:2806–2831.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association*, 1(1):114–125.

Herweg, F. et al. (2024). Axiom preferences and choice mistakes under risk.

Hey, J. D. (2001). Does repetition improve consistency? *Experimental Economics*, 4(1):5–54.

Humphrey, S. J. and Kruse, N.-Y. (2024). Who accepts savage's axiom now? *Theory and Decision*, 96(1):1–17.

Kuzmics, C., Rogers, B., and Zhang, X. (2020). Is ellsberg behavior evidence of ambiguity aversion? Working paper.

MacCrimmon, K. and Larsson, S. (1979). Utility theory: Axioms versus "paradoxes". In Allais, M. and Hagen, O., editors, *Expected Utility Hypotheses and the Allais Paradox*, pages 333–409. Reidel.

MacCrimmon, K. R. (1968). Descriptive and normative implications of the decision-theory postulates. In Borch, K. and Mossin, J., editors, *Risk and Uncertainty*, pages 3–32. Springer, New York.

Martínez-Marquina, A., Niederle, M., and Vespa, E. (2019). Failures in contingent reasoning: The role of uncertainty. *American Economic Review*, 109(10):3437–3474.

McNeil, B. J., Pauker, S. G., and Tversky, A. (1988). On the framing of medical decisions. In Bell, D. E., Raiffa, H., and Tversky, A., editors, *Decision Making: Descriptive, Normative, and Prescriptive Interactions*, pages 562–568. Cambridge University Press, Cambridge.

Miller, P. M. and Fagley, N. S. (1991). The effects of framing, problem variations, and providing rationale on choice. *Personality and Social Psychology Bulletin*, 17(5):517–522.

Moskowitz, H. (1974). Effects of problem representation and feedback on rational behavior in allais and morlat-type problems. *Decision Sciences*, 5:225–242.

Nicholls, N., Romm, A. T., and Zimper, A. (2015). The Impact of Statistical Learning on Violations of the Sure-thing Principle. *Journal of Risk and Uncertainty*, 50(2):97–115.

Nielsen and Rehbeck (2022). When choices are mistakes. *American Economic Review*, 112(7):2237–2268.

Sieck, W. and Yates, J. F. (1997). Exposition effects on decision making: Choice and confidence in choice. *Organizational Behavior and Human Decision Processes*, 70(3):207–219.

Slovic, P. and Tversky, A. (1974). Who accepts savage's axiom? *Behavioral Science*, 19(6):368–373.

van de Kuilen, G. (2009). Subjective probability weighting and the discovered preference hypothesis. *Theory and Decision*, 67(1):1–22.

van de Kuilen, G. and Wakker, P. P. (2006). Learning in the allais paradox. *Journal of Risk and Uncertainty*, 33(3):155–164.

Wu, K., Fehr, E., Hofland, S., and Schonger, M. (2023). On the psychological foundations of ambiguity and compound risk aversion. CESifo Working Paper 11150, CESifo.

Yu, C. W., Zhang, Y. J., and Zuo, S. X. (2021). Multiple switching and data quality in the multiple price list. *Review of Economics and Statistics*, 103:136–150.

Welcome to this experiment

Thank you for participating in this experiment!

Please read the instructions carefully, because your earnings from this experiment will depend on how well you understood the instructions.

Please read each question carefully and make your choices accordingly.

There are no right or wrong answers.

Incentives and Payment

This experiment consists of **7 questions**.

Out of these 7:

- **3 questions will be randomly selected to be incentivised** (i.e., eligible for real payment),
- The other **4 will not affect your payment**.

At the end of the experiment:

- **One of the 3 incentivised questions will be randomly chosen** with equal probability (1 in 3),
- Your payoff will depend solely on your choice in that question.

Payment

Your payment will be completed in the form of Amazon vouchers. The vouchers will be sent to the email address you provided once all sessions are completed.

If you have any questions please feel free to ask any of the experimenters by sending an email at k.georgalos@lancaster.ac.uk

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact the experimenter: Dr Konstantinos Georgalos (k.georgalos@lancaster.ac.uk)

If you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact: Professor Hilary Ingham (Head of Economics Department, h.ingham@lancaster.ac.uk).

When you are ready, complete your details below and press the button below to start the experiment. We need this information only to process your payment. By participating to this experiment means you consent to the use of your anonymised choice data for the use of academic research purposes.

Please enter your information:

First Name

Surname

Student Number

Start

Question 1

🎲 Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

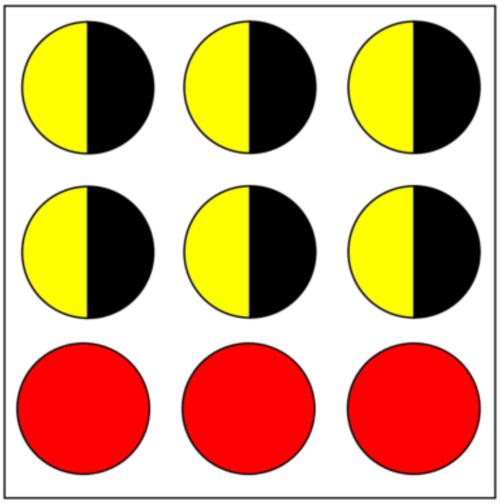
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- (●) Win £8 if the ball is Red 🔴, otherwise £0
- ( ) Win £8 if the ball is Black ⚫, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident)

3

0 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice)

4.00

0.00 8.00

Submit

Question 2

🎲 Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

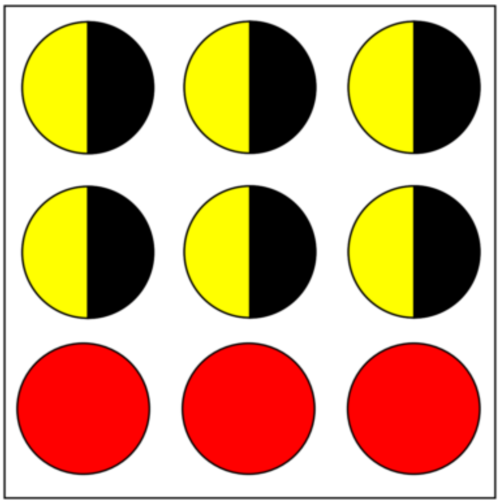
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- (●) Win £8 if the ball is Red 🔴 or Yellow 🟡, otherwise £0
- ( ) Win £8 if the ball is Black ⚫ or Yellow 🟡, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident) ⓘ

3

0 — 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice) ⓘ

4.00

0.00 — 8.00

Submit

Manage app

Question 2

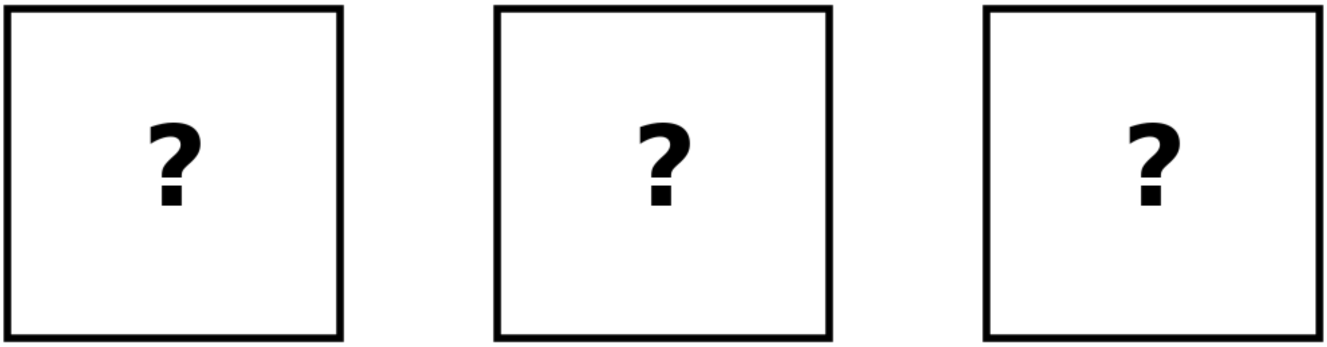
Imagine you are a contestant on a game show.

You are presented with **three closed doors**. Behind **one of the doors** is a **car**, and behind the other **two doors**, there is **nothing**.

You must choose **one door**.

Before you make any further decisions:

> **What is the probability that the car is behind Door 1, Door 2, or Door 3?**



Door 1

Door 2

Door 3

Submit

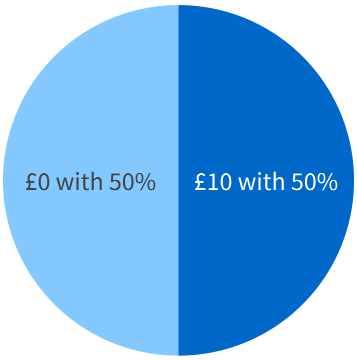
Question 3

Consider the following two lotteries:

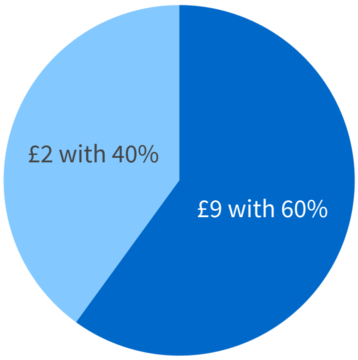
Lottery A pays **£10** with probability **0.5** and **£0** with probability **0.5**.

Lottery B pays **£9** with probability **0.6** and **£2** with probability **0.4**.

Lottery A



Lottery B



Which lottery do you prefer?

- Lottery A
- Lottery B

Submit

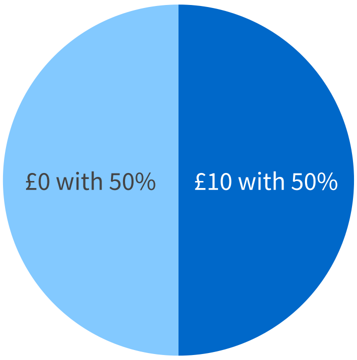
Question 3

Consider the following two lotteries:

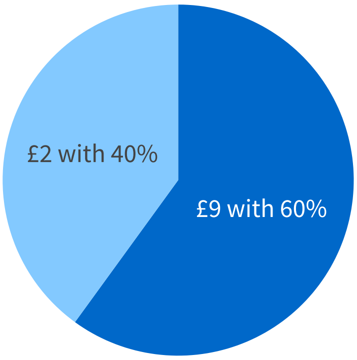
Lottery A pays **£10** with probability **0.5** and **£0** with probability **0.5**.

Lottery B pays **£9** with probability **0.6** and **£2** with probability **0.4**.

Lottery A



Lottery B



What influenced your decision? (Select up to 2 reasons)

- [ ] How likely the outcomes are to occur.
- [ ] How much I value the monetary outcomes.
- [ ] How familiar or comfortable the option feels to me.
- [ ] How risky the option feels, regardless of actual probabilities.

Submit

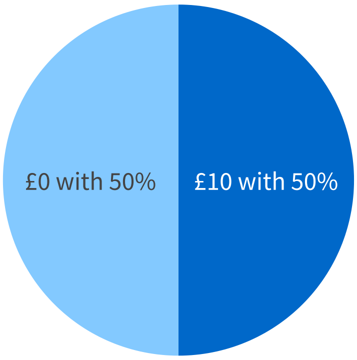
Question 3

Consider the following two lotteries:

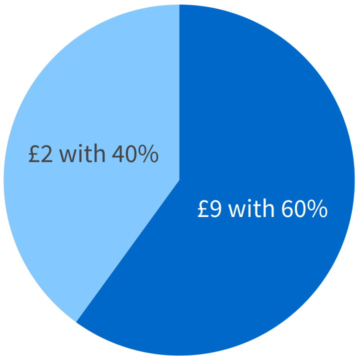
Lottery A pays **£10** with probability **0.5** and **£0** with probability **0.5**.

Lottery B pays **£9** with probability **0.6** and **£2** with probability **0.4**.

Lottery A



Lottery B



Why did you not select one of the first two reasons (likelihood or value of outcome)?

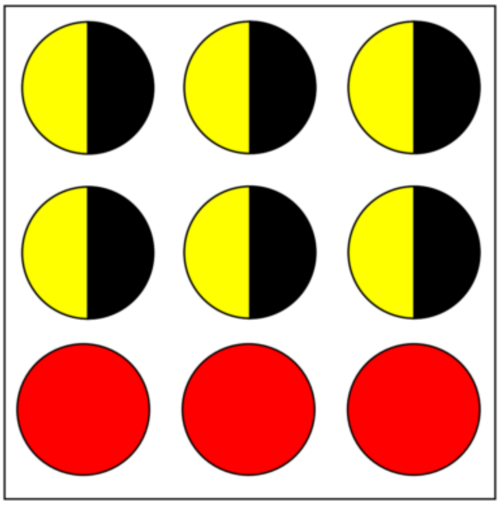
Reason:

Submit

Question 4

Continuing from the box example:
Since the monetary outcomes for all options are exactly the same, your decision depends **solely on the probability** of each event occurring (i.e., drawing a ball of a particular color).

Clearly, since we know there are **3 red balls** in the box, the probability of drawing a red ball is **33.3%** (3 out of 9, or 1/3).



What do you think is the probability of drawing a black ball?"

Submit

Question 5

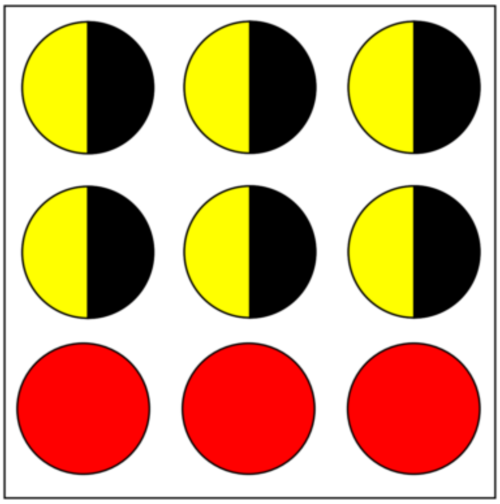
You know that the chance of drawing a **red ball** is 33.3% (3 out of 9).
You might also believe that the chance of drawing a **black ball** is about the same — 33.3%.

Now think about this:

Would you say the red ball probability feels **more reliable**,
just because you know for sure there are 3 red balls in the box?

Do you feel **less sure** about the black ball probability,
since it depends on an unknown number of black balls (between 0 and 6)?

Is that uncertainty why you might be **less willing to bet on black**?



Choose your answer:

Submit

Question 6

This question may be randomly selected to determine your actual payment at the end of the experiment.

You know that there are 9 balls in the box — red, black, and yellow.

In this question, you will be shown a number of **scenarios** with different possible quantities of **red balls** in the box.
In each scenario, you will be asked to **bet on black balls**.

For each scenario, you will see a list of choices between two options, like the one below:

Black ball from the box	☐ A	☐ B	£8 with probability 1 out of 9 (11.1%)
Black ball from the box	☐ A	☐ B	£8 with probability 2 out of 9 (22.2%)
Black ball from the box	☐ A	☐ B	£8 with probability 3 out of 9 (33.3%)
Black ball from the box	☐ A	☐ B	£8 with probability 4 out of 9 (44.4%)
Black ball from the box	☐ A	☐ B	£8 with probability 5 out of 9 (55.6%)
Black ball from the box	☐ A	☐ B	£8 with probability 6 out of 9 (66.7%)

- **Option A**: A fixed lottery that pays £8 **if a black ball** is drawn from the box.
- **Option B**: A lottery that pays £8 with a **specified chance** (e.g., 2 out of 9, or ~22.2%).

Note that **Option A** always remains the same — it depends on the number of black balls in the box, which is **unknown** to you.

Option B, on the other hand, changes across the rows: the probability of winning gradually increases.

For each row, choose the option you **prefer**, depending on what you believe the likelihood is that a black ball is in the box.

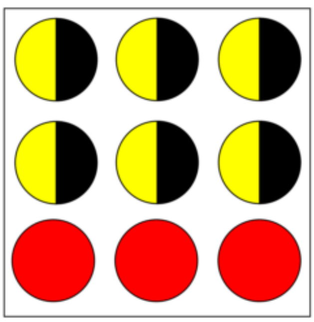
In the example above, the participant chose Option A (drawing from the box) for the first 5 rows,
and Option B (the fixed lottery) for the rest.
This implies they believe the probability of drawing a black ball from the box is **less than 55.6%**.

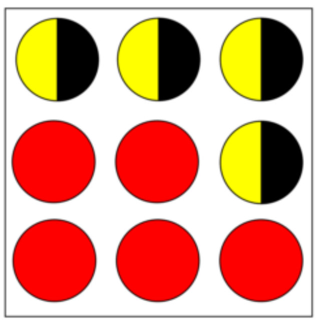
If this question is selected to be played for real, the software will **randomly choose one of the scenarios**,
and then **randomly select one of the 10 rows** within that scenario.

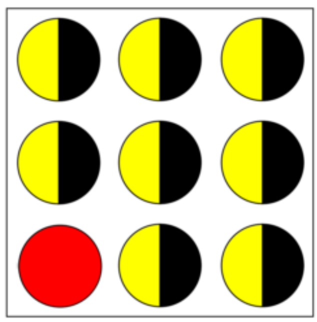
- If you chose **Option A** for the selected row, the software will draw a ball from the box.
  If the ball is **black**, you will win **£8**; otherwise, you will win nothing.
- If you chose **Option B**, the software will generate a random number between **0 and 100**.
  If this number is **less than the winning probability** shown in that row, you win **£8**; otherwise, you win nothing. For example, in the list above, if row 6 is chosen to be played for real, where the choice is B, if the random generated number is less that 55.6, then you win £8.

Please complete your choices for each of the three scenarios.

Scenarios







Scenario 1 – there are 3 red balls in the box

Black ball from the box	☐ A	☐ B	£8 with probability 0 out of 9 (0.0%)
Black ball from the box	☐ A	☐ B	£8 with probability 1 out of 9 (11.1%)
Black ball from the box	☐ A	☐ B	£8 with probability 2 out of 9 (22.2%)
Black ball from the box	☐ A	☐ B	£8 with probability 3 out of 9 (33.3%)
Black ball from the box	☐ A	☐ B	£8 with probability 4 out of 9 (44.4%)
Black ball from the box	☐ A	☐ B	£8 with probability 5 out of 9 (55.6%)
Black ball from the box	☐ A	☐ B	£8 with probability 6 out of 9 (66.7%)
Black ball from the box	☐ A	☐ B	£8 with probability 7 out of 9 (77.8%)
Black ball from the box	☐ A	☐ B	£8 with probability 8 out of 9 (88.9%)
Black ball from the box	☐ A	☐ B	£8 with probability 9 out of 9 (100.0%)

Scenario 2 – there are 5 red balls in the box

Black ball from the box	☐ A	☐ B	£8 with probability 0 out of 9 (0.0%)
Black ball from the box	☐ A	☐ B	£8 with probability 1 out of 9 (11.1%)
Black ball from the box	☐ A	☐ B	£8 with probability 2 out of 9 (22.2%)
Black ball from the box	☐ A	☐ B	£8 with probability 3 out of 9 (33.3%)
Black ball from the box	☐ A	☐ B	£8 with probability 4 out of 9 (44.4%)
Black ball from the box	☐ A	☐ B	£8 with probability 5 out of 9 (55.6%)
Black ball from the box	☐ A	☐ B	£8 with probability 6 out of 9 (66.7%)
Black ball from the box	☐ A	☐ B	£8 with probability 7 out of 9 (77.8%)
Black ball from the box	☐ A	☐ B	£8 with probability 8 out of 9 (88.9%)
Black ball from the box	☐ A	☐ B	£8 with probability 9 out of 9 (100.0%)

Scenario 3 – there are 1 red balls in the box

Black ball from the box	☐ A	☐ B	£8 with probability 0 out of 9 (0.0%)
Black ball from the box	☐ A	☐ B	£8 with probability 1 out of 9 (11.1%)
Black ball from the box	☐ A	☐ B	£8 with probability 2 out of 9 (22.2%)
Black ball from the box	☐ A	☐ B	£8 with probability 3 out of 9 (33.3%)
Black ball from the box	☐ A	☐ B	£8 with probability 4 out of 9 (44.4%)
Black ball from the box	☐ A	☐ B	£8 with probability 5 out of 9 (55.6%)
Black ball from the box	☐ A	☐ B	£8 with probability 6 out of 9 (66.7%)
Black ball from the box	☐ A	☐ B	£8 with probability 7 out of 9 (77.8%)
Black ball from the box	☐ A	☐ B	£8 with probability 8 out of 9 (88.9%)
Black ball from the box	☐ A	☐ B	£8 with probability 9 out of 9 (100.0%)

Question 7

🎲 Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

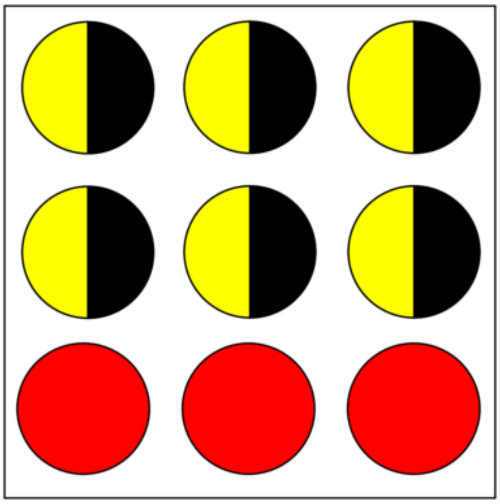
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- ◯ Win £8 if the ball is Red 🔴, otherwise £0
- ◯ Win £8 if the ball is Black ⚫, otherwise £0

Submit

Question 7

Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

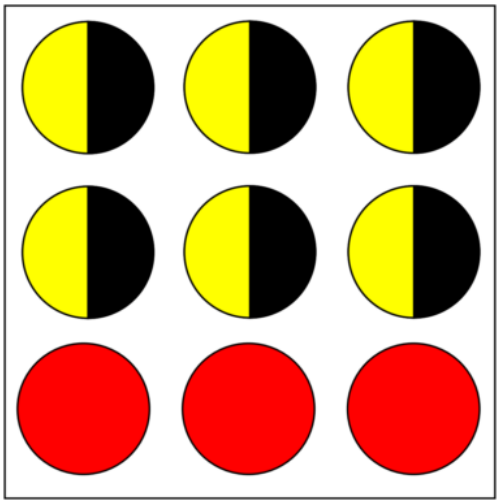
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- ( ) Win £8 if the ball is Red or Yellow, otherwise £0
- (•) Win £8 if the ball is Black or Yellow, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident)

3

0 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice)

4.00

0.00 8.00

Submit

Final Questions

Age

17

Gender

Field of study

What do you think the purpose of the experiment is?

Did you face any difficulties during the experiment? Do you have any comments?

Submit

Welcome to this experiment

Thank you for participating in this experiment!

Please read the instructions carefully, because your earnings from this experiment will depend on how well you understood the instructions.

Please read each question carefully and make your choices accordingly.

There are no right or wrong answers.

Incentives and Payment

This experiment consists of **7 questions**.

Out of these 7:

- **3 questions will be randomly selected to be incentivised** (i.e., eligible for real payment),
- The other **4 will not affect your payment**.

At the end of the experiment:

- **One of the 3 incentivised questions will be randomly chosen** with equal probability (1 in 3),
- Your payoff will depend solely on your choice in that question.

Payment

Your payment will be completed in the form of Amazon vouchers. The vouchers will be sent to the email address you provided once all sessions are completed.

If you have any questions please feel free to ask any of the experimenters by sending an email at k.georgalos@lancaster.ac.uk

If you have any queries or if you are unhappy with anything that happens concerning your participation in the study, please contact the experimenter: Dr Konstantinos Georgalos (k.georgalos@lancaster.ac.uk)

If you have any concerns or complaints that you wish to discuss with a person who is not directly involved in the research, you can also contact: Professor Hilary Ingham (Head of Economics Department, h.ingham@lancaster.ac.uk).

When you are ready, complete your details below and press the button below to start the experiment. We need this information only to process your payment. By participating to this experiment means you consent to the use of your anonymised choice data for the use of academic research purposes.

Please enter your information:

First Name

Surname

Student Number

Start

Question 1

Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

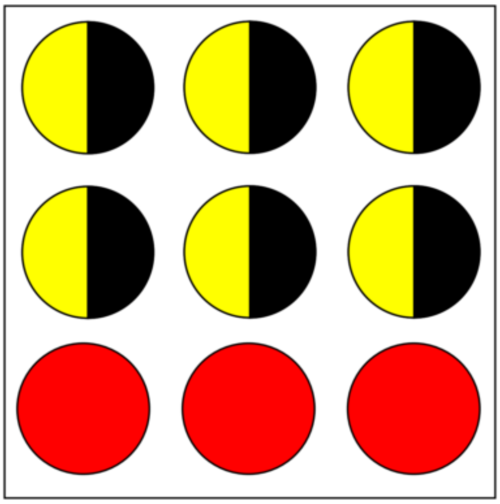
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- (•) Win £8 if the ball is Red, otherwise £0
- ( ) Win £8 if the ball is Black, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident)

3

0 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice)

4.00

0.00 8.00

Submit

Question 2

🎲 Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

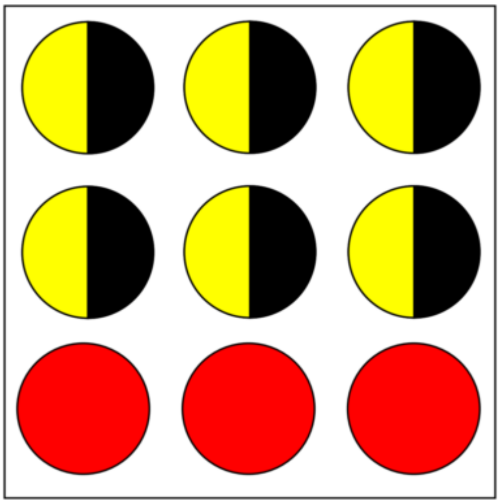
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** — but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box, in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- (●) Win £8 if the ball is Red 🔴 or Yellow 🟡, otherwise £0
- ( ) Win £8 if the ball is Black ⚫ or Yellow 🟡, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident) ⓘ

3

0 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice) ⓘ

4.00

0.00 8.00

Submit

Question 3

In what follows you will be presented with a short tutorial on the **Raven's Progressive Matrices** test.

The Raven's Progressive Matrices test is a nonverbal assessment designed to measure abstract reasoning and fluid intelligence. Developed by John C. Raven in 1936, it presents a series of visual puzzles where the test-taker must identify the missing piece that completes a pattern in a grid of shapes or symbols. The complexity increases progressively, requiring individuals to analyze relationships between shapes, sequences, and transformations. Since it relies on pattern recognition rather than language or prior knowledge, it is widely used across cultures to assess general cognitive abilities.

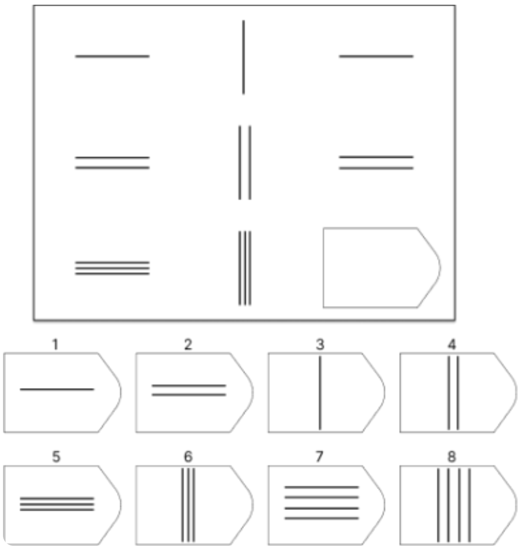
We will now show you some basic strategies for solving Raven matrices. Then, you'll have a chance to complete one example taken from the actual test.

In each test item, you're shown a pattern of shapes arranged in a 2×2, 3×3, or 4×4 matrix. One piece is missing, and your task is to identify which of the given options correctly completes the pattern.

Consider, for example, the 3×3 matrix below. The bottom-right element is missing, and you're asked to select the correct option from 1 to 8. To solve it, you need to find the pattern that explains how the shapes change across the rows and columns. These changes may involve shape, size, number, shading, orientation, or position.

Often, more than one pattern is used at the same time. By spotting these patterns, you can determine which option fits best. At the bottom of the page we provide a list of the 5 basic change patterns.

Let us try to identify the change patterns in the matrix:



Look at the shapes across columns, from left to right. What changes?

Submit

The 5 Patterns of Raven's Advanced Progressive Matrices

The objects on the Raven Advanced Progressive Matrices Test usually follow one or more of 5 basic change patterns. Here are the 5 fundamental patterns:

Rotation

In the rotation pattern, objects across the rows or columns rotate in a certain pattern. This pattern may be constant (e.g. 90 degrees) or changing (e.g. 45, 90, 135 degrees, etc.).

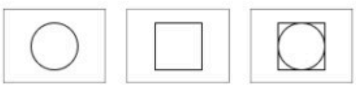
Progression

The progression pattern is a rather broad definition for a change in object that is not self-evident. This pattern requires most experience and practice to recognize, since it is so versatile.

Examples may be: number of shapes' sides, number of visible elements, colouring, and more

Construction

The construction pattern, which in the language of the Raven APM test is named "combination" is a construction of two objects in the row or column under certain rules to create the third.

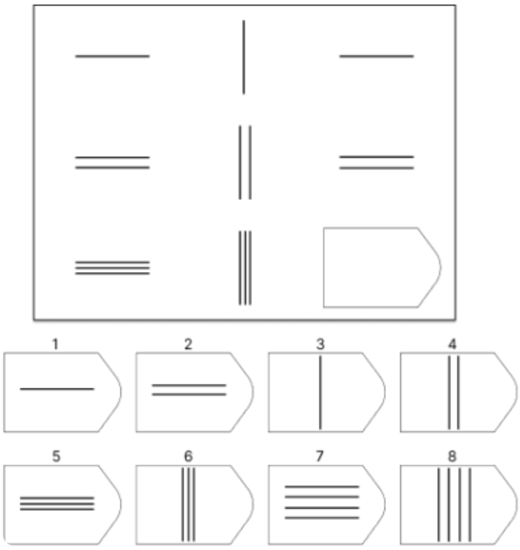


Motion

Manage app

Question 4

Consider again the same matrix as before. Now, based on the two previous patterns, which shape completes the matrix?.

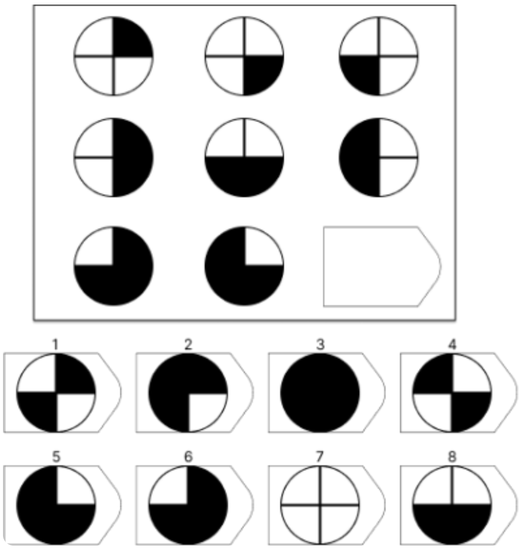


Please choose your answer?

Submit

Question 5

Consider the following matrix. In this matrix there are two different changing patterns: motion and progression. The pattern across the columns (left-to-right) is **motion** (in each step, a different quarter of the circle is coloured). The pattern down the rows (top-to-bottom) is **progression** (in each step, an additional quarter of the circle is coloured). Based on this, which option completes the matrix:

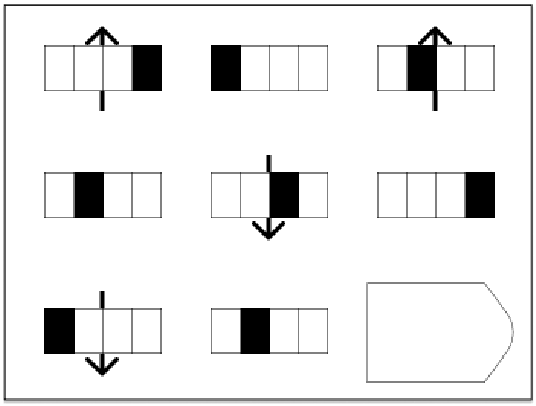


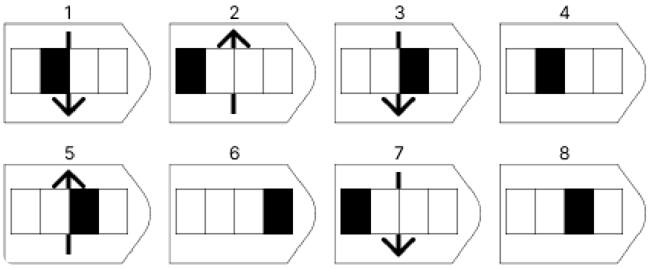
Please choose your answer?

Submit

Question 6

Consider the following matrix. In this matrix there are two different changing patterns: motion and progression. The pattern across the columns (left-to-right) is **motion** (in each step, a different square is coloured). The pattern down the rows (top-to-bottom) is **progression** (in each step, the arrow rotates). Based on this, which option completes the matrix:





Please choose your answer?

Submit

Question 7

🎲 Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

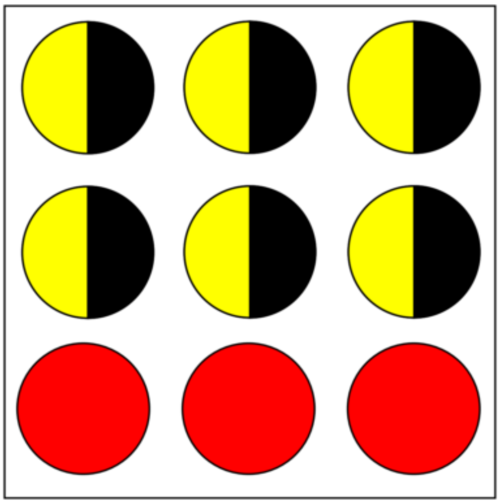
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- ○ Win £8 if the ball is Red 🔴, otherwise £0
- ◉ Win £8 if the ball is Black ⚫, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident) ⓘ

3

0 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice) ⓘ

4.00

0.00 8.00

Submit

Question 7

🎲 Task Description

This question may be randomly selected to determine your actual payment at the end of the experiment.

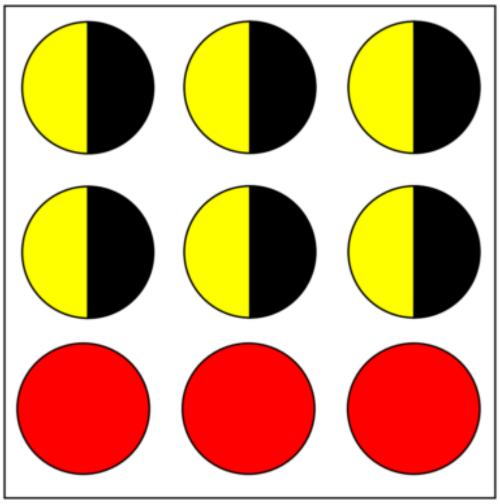
Consider a box containing **9 balls**, as shown below:

- Exactly **3 balls are red**.
- The remaining **6 balls are either yellow or black**, in an **unknown proportion**.
- This means the number of black (or yellow) balls can range from **0 to 6** —
  but you are only told that the **total number of black and yellow balls is 6**.

The software is programmed to **simulate a random draw** from this box,
in a way similar to how a person would draw a ball at random.

You will be asked to **place a bet on the colour** of the ball that will be drawn.

If you choose to bet on a colour and the ball drawn matches this colour, you win the prize.



Which option do you prefer?

- ○ Win £8 if the ball is Red 🔴 or Yellow 🟡, otherwise £0
- ◉ Win £8 if the ball is Black ⚫ or Yellow 🟡, otherwise £0

How confident are you about your choice? (0 = Not confident at all, 7 = Very confident)

3

0 7

Hypothetically speaking, how much would we need to pay you to switch to the *other* option? (£0 = I am relatively indifferent; £8 = I strongly prefer my choice)

4.00

0.00 8.00

Submit

Final Questions

Age

17

Gender

Field of study

What do you think the purpose of the experiment is?

Did you face any difficulties during the experiment? Do you have any comments?

Submit