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Pupil and Neural Dynamics Reveal Belief-Dependent Decision Making Under Ambiguity

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eLife Assessment

This study presents a **useful** combined analysis of human behavior, pupillometry and EEG measures to probe differences in ambiguity assessment between individuals during value-based decision-making. Using computational models, the authors aim to test for distinct groups of participants that differ in the relationship between evidence accumulation, arousal, and neural decision-making computations. However, at present, the evidence for group differences in the physiological, neural, and behavioral profile of decision-making under uncertainty is **incomplete**, lacking an appropriate statistical test for group differences, and a more complete assessment of the modeling results on evidence accumulation in decision-making in this study is required to robustly characterize and interpret the results.

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Abstract

Humans make thousands of decisions under ambiguity every day, where most times the probabilities of getting beneficial outcomes are not fully known. Although ambiguity aversion is well characterized at the aggregate level, it remains unclear how individuals internally represent ambiguous outcomes and how these representations shape behavior and physiology. To address these questions, we investigate value-based decision-making under risk and ambiguity using a multimodal approach that combines behavioral, pupillometric, and electroencephalographic (EEG) data. We show that individuals adopt distinct decision strategies that reflect different internal beliefs about unknown outcomes. These belief differences are expressed not only in choice but also in pupil-linked arousal during decision formation. Crucially, physiological differences across strategies persist under an objective valuation rule for ambiguous options but disappear when valuation is computed using each individual's subjective beliefs, indicating that arousal tracks subjective belief rather than objective task structure. Together, our findings show that ambiguity aversion is not a uniform bias but reflects heterogeneous internal belief models, and that multimodal physiology provides a window into the mechanisms through which these beliefs guide value-based choice.

1 Introduction

Humans make decisions in situations where outcomes are unknown, and the probabilities of benefit and harm are incomplete or unknown. Such decisions shape behavior across many domains, including financial investment, medical decision making, social interaction, and collaboration with artificial intelligence systems. A key distinction is between *risk*, where outcome probabilities are known, and *ambiguity*, where outcome probabilities cannot be precisely

determined (15; 37; 36). For example, risk is betting on a fair coin toss, whereas ambiguity is betting on a coin drawn from a set of coins with different and unknown biases. Ambiguity poses a distinct cognitive challenge and often elicits behavioral responses that differ from those observed under risk (37; 3; 64). Understanding how individuals interpret and respond to ambiguity, and the underlying computational and neurophysiological mechanisms that give rise to these responses, is therefore central to explaining human decision-making in naturalistic settings.

A central distinction in decision theory separates decisions under risk from decisions under ambiguity. Under risk, outcome probabilities are known; under ambiguity, they are partially or entirely unknown. The behavioral consequences of this distinction were first formalized by the Ellsberg paradox, which showed that people systematically prefer risky options with known probabilities over ambiguous options with unknown probabilities, even when the expected values are equivalent (18). Subsequent work across economics, psychology, and neuroscience has consistently demonstrated ambiguity aversion, often interpreted as a general bias against unknown probabilities (14; 3; 11). However, much of this literature focuses primarily on choice behavior, characterizing how often individuals avoid ambiguity, while leaving open questions about how ambiguity is internally represented and processed during decision formation.

Despite robust population-level evidence for ambiguity aversion, aggregate choice patterns can obscure substantial inter-individual differences. People vary widely in risk tolerance, learning strategies, and how they form beliefs about unknown outcomes (19). Yet ambiguity aversion is often treated as a single bias or a fixed trait that applies uniformly across individuals (1; 14; 33; 31). This perspective overlooks the possibility that different people may hold qualitatively different internal representations of ambiguity, even when they face the same objective risk. Moreover, population-level analyses rarely link behavioral variability to corresponding physiological or neural responses that could reveal how ambiguity is processed internally. As a result, it remains unclear what individuals actually believe when probabilities are unknown.

Physiological measures offer a powerful window into the internal processes that underlie decision-making under risk. Pupil size provides a sensitive index of arousal and valuation, particularly in value-based decision tasks where it tracks risk, surprise, and subjective value (45; 22; 56; 62; 23). Electrophysiological signal complements this by revealing the temporal dynamics of neural processes related to control, attention, and valuation during decision formation (27; 35; 44; 50; 40). Prior work has linked both pupillary and EEG signals to uncertainty, cognitive conflict, effort, and attentional engagement (26; 9; 61). However, these physiological signatures are rarely combined with explicit inference of individuals' internal beliefs about ambiguous outcomes. As a result, it remains unclear whether physiological signals reflect objective properties of risk or the subjective beliefs individuals hold when probabilities are unknown.

Behavioral choices alone provide an incomplete picture of how decisions under ambiguity are formed. Similar choices can arise from different internal beliefs or computational strategies, making it difficult to infer how risk is represented from behavior alone (14; 19). Trial-level physiological measures offer a complementary approach by capturing internal states as decisions unfold. However, it remains unclear whether and how these physiological dynamics reflect the latent belief models that individuals use to interpret ambiguous outcomes, and whether they can explain stable individual differences in ambiguity processing beyond what is observable from aggregate choice patterns.

To address these questions, we developed a value-based decision-making task with controlled levels of ambiguity and simultaneously multi-modal physiological recordings. Participants chose between a sure option and a lottery with partially unknown outcome probabilities while pupil size and EEG were measured throughout the decision process. Using behavior under non-ambiguous conditions, we characterized participants into three decision styles (*ideal*, *aggressive*, and *conservative*) based on how their choices aligned with expected-value optimality. We then inferred subjective belief parameters that captured how individuals internally interpreted the ambiguous probability mass and examined how these beliefs related to choice behavior, arousal dynamics, and neural activity. This multimodal framework allowed us to study ambiguity processing at the level of individual belief models rather than aggregate choice patterns.

We identify distinct decision styles under ambiguity that reflect stable internal belief models rather than random variability or uniform bias. Our results indicate that behavioral asymmetries across individuals are explained by differences in subjective beliefs about ambiguous outcomes: *aggressive* participants exhibit optimistic valuation, *conservative* participants exhibit pessimistic valuation, and *ideal* participants occupy an intermediate regime. Crucially, physiological signals validate these belief models. Pupil-linked arousal tracks subjective valuation rather than objective expected value, and neural dynamics reveal belief-specific computational regimes involving control, excitability, and engagement. Together, these findings provide a belief-level and computational account of how ambiguity is represented, evaluated, and acted upon by individuals, linking internal beliefs to behavior and physiology in value-based decision making. Notably, individual decision strategies expressed in this non-collaborative task are also associated with leadership tendencies observed in prior team-based interactions, suggesting broader relevance beyond isolated choice behavior.

2 Results

2.1 Task Structure and Behavioral Stratification

Participants first completed a three-person collaborative spacecraft control task requiring real-time coordination across distinct degrees of freedom under partial and complementary visual information (48). They then individually performed a valuebased decision-making task (Lottery Choice Task, LCT; Fig. 1a) designed to dissociate decision formation under *risk* and *ambiguity*.

On each trial, participants chose whether to *keep* a sure endowment or *invest* it into a lottery whose outcomes consisted of an explicit gain and loss (Fig. 1b). In zero ambiguity (**risk** only) trials, the gain, loss, and their associated probabilities were fully specified, allowing the expected value (EV) of the investment option to be computed from complete information. In **ambiguity** trials, the payoff magnitudes remained explicit, but the probability of receiving the gain or loss was only partially specified: the task masked a portion of the probability mass, leaving participants with an interval rather than a single known probability (Fig. 1c). Ambiguity differs fundamentally from risk at both the physiological level (34; 6) and the behavioral level (37; 4).

Throughout the paper, we treat participants' investment behavior under zero ambiguity trials as a behavioral proxy for decision strategy. Under this framing, different decision strategies reflect distinct decision policies governing valuation and action selection. To quantify inter-individual variation, we classified participants into three investor types based on how their choices aligned with the expected-value–optimal action across risk trials (Fig. 1d; see *Materials and Methods*, Section 4.3). This procedure yielded three exclusive groups: *ideal*, *aggressive*, and *conservative* investors. This stratification operationalizes individual decision policy using stable differences in investment behavior under known risk, enabling subsequent analyses of how these strategies generalize to ambiguity and shape physiological responses.

2.2 Behavioral and Physiological Response to Different Ambiguity

We examined how ambiguity modulated investment behavior across decision strategies (Fig. 2a). Consistent with classical ambiguity aversion as formalized in the Ellsberg paradox (18; 14), increasing ambiguity was associated with a systematic reduction in the probability of choosing to

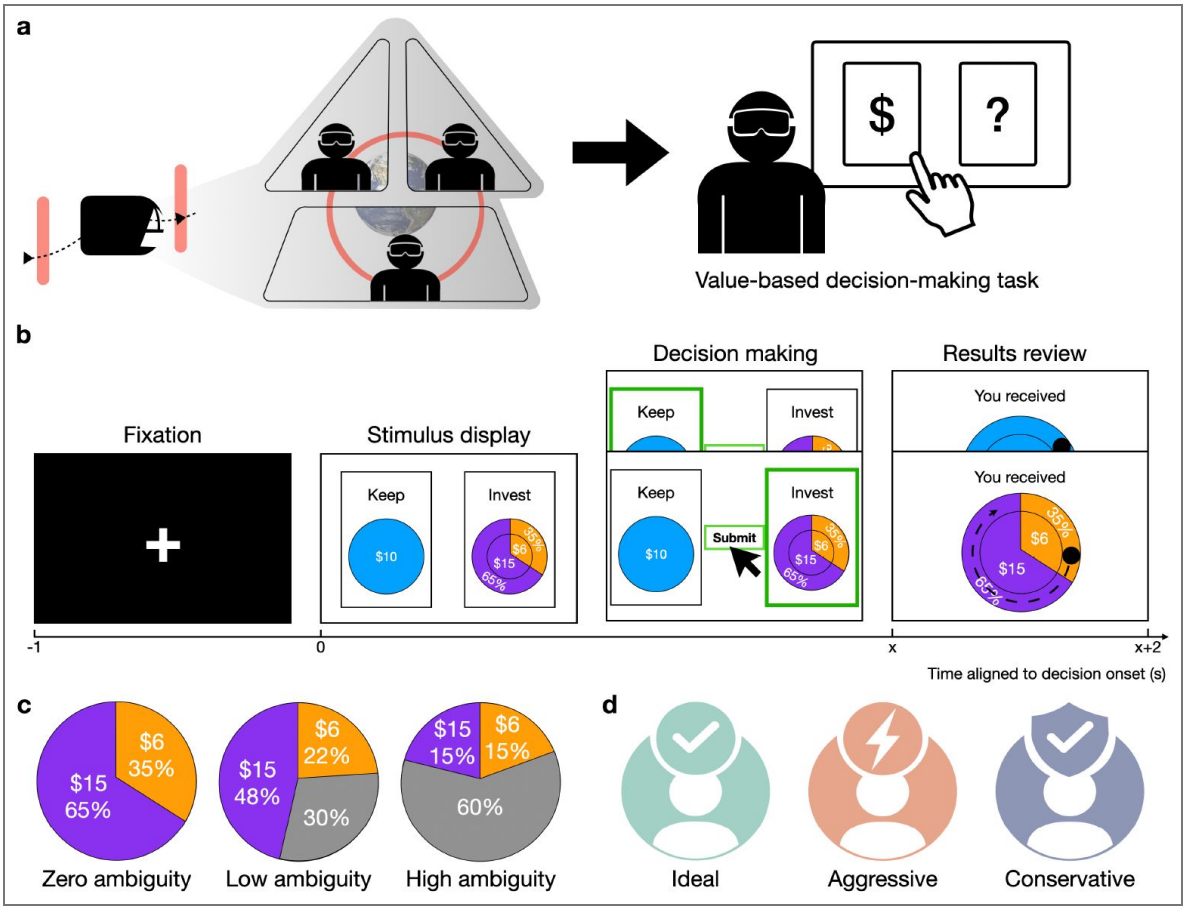

Fig. 1. Experimental setup.

a, Three participants first perform a collaborative space craft control task. In this task, three participants with different perspectives control a single degree of freedom of the spacecraft movement toward earth, coordinate through communication while avoiding obstacles. Afterward, each participant completed the Lottery Choice Task (LCT) individually. **b**, The temporal structure of a single trial of the LCT. The horizontal axis denotes time in seconds, and analyses were time-locked to stimulus onset. Each trial started with a 1 s fixation. Then, the stimulus was presented, and participants had up to 5 s to make a *keep* or *invest* decision ($x \leq 5$). Outcome feedback was then revealed for 2 s following the decision, after which the next trial began with a fixation period. The values and risk probabilities shown in panels **b** and **c** are illustrative examples. **c**, Trials varied in ambiguity level. Under zero ambiguity, risk probability is fully known to participants. Under low (30%) or high (60%) ambiguity, partial risk is unknown when making decisions. **d**, Based on participants investment decisions across trials, they were categorized as *Ideal*, *Aggressive*, or *Conservative*.

invest. This effect was pronounced in both *ideal* and *aggressive* investors: the majority of participants in these two groups showed a steep decline in investment rates as ambiguity increased from 0% to 60% (Fig. 2b, χ^2 tests for ambiguity effects: 78.12% of *ideal* participants and 84.38% of *aggressive* participants exhibited a significant effect, $P < 0.05$). In contrast, *conservative* investors showed substantially weaker sensitivity to ambiguity. Their investment probability was already low at 0% ambiguity and decreased only modestly as ambiguity increased (46.88%). As a result, under high ambiguity, investment behavior converged across groups, whereas under low ambiguity, *ideal* and *aggressive* investors remained substantially more willing to invest than *conservative* investors. These results indicate that ambiguity exerts strong and graded control over value-based decisions, but that this control is selectively attenuated in individuals with conservative decision strategies.

Ambiguity also shaped the temporal dynamics of decision making (Fig. 2c). Across *ideal* and *aggressive* investors, decision time increased systematically with higher ambiguity (mixed effect model, *ideal* $\beta = 0.03$, $P < 0.001$; *aggressive* $\beta = 0.07$, $P < 0.0001$), indicating that resolving partially unknown probabilities required additional deliberation. In contrast, *conservative* investors exhibited consistently long decision times across all ambiguity levels, with no significant modulation by ambiguity ($\beta = 0.01$, $P = 0.2745$). As a result, group differences in decision time were stable as ambiguity increased. These findings suggest that while ambiguity imposes an additional temporal cost on the decision process for *ideal* and *aggressive* investors, *conservative* investors operate in a uniformly slow decision regime that is insensitive to changes in ambiguity.

Ambiguity further modulated pupil-indexed physiological arousal. For both *ideal* and *conservative* investors, ambiguous trials elicited significantly larger pupil size changes than non-ambiguous trials, indicating heightened arousal under conditions of partial ambiguity (Fig. 2d). This pattern is consistent with prior work linking pupil dilation to affective and arousal responses during decision making under ambiguity (45; 22; 56; 30). In contrast, *aggressive* investors showed no significant pupil modulation by ambiguity, with pupil responses remaining near baseline across the full decision window. This reduced physiological sensitivity align with shorter decision time (Fig. 2c) indicates that *aggressive* participants' arousal level are less modulated by ambiguity. Together, these results suggest that ambiguity engages arousal systems in *ideal* and *conservative* investors, whereas *aggressive* investors exhibit a blunted arousal response to ambiguity that aligns with their stable, low-risk decision policy.

2.3 Physiological Response Differences for Different Investment Decisions

After establishing how ambiguity modulates behavior and pupil-linked arousal across decision strategies, we next examined how physiological responses differ between *keep*and *invest* decisions. Because participants' decision strategies were defined using non-ambiguous trials, subsequent physiological comparisons were restricted to ambiguous trials to avoid circularity. This allowed us to isolate decision-specific physiological signatures under ambiguity, independent of the criteria used to characterize individual decision strategies.

2.3.1 Anticipatory and Choice-Dependent Pupil Arousal Signatures

Pupil size dynamics revealed robust decision-dependent arousal signatures that were consistent across decision strategies. In all three groups, pupil responses diverged systematically between *keep*and *invest* choices following decision onset, with *keep* decisions exhibiting larger pupil size changes than *invest* decisions throughout the subsequent two-second decision window (Fig. 3a). This time-locked separation indicates that pupil-linked arousal tracks evolving decision commitment rather than reflecting a static baseline difference. Such decision-dependent pupil modulation is consistent with prior work showing that pupil dilation reflects subjective belief states and uncertainty during value-based choices (45), and more broadly aligns with evidence linking task-evoked pupil dilation to phasic locus coeruleus–norepinephrine (LC–NE) activity during the decision process and behavioral engagement (58).

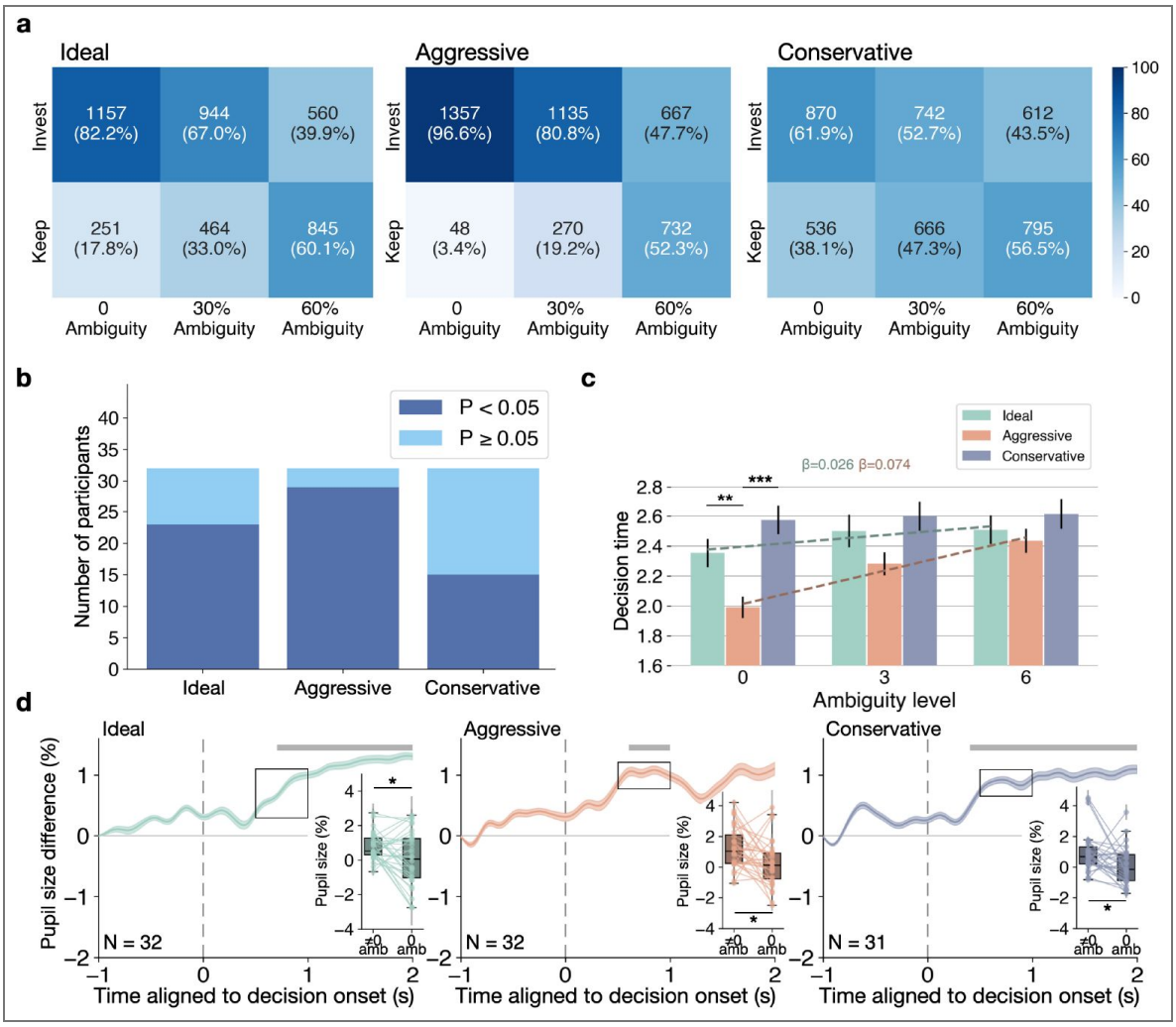

Fig. 2. Behavioral and pupil signatures across decision strategies under ambiguity.

a, Investment behavior across ambiguity levels (0%, 30%, 60%) for *ideal, aggressive*, and *conservative* investors. Heatmaps show the number and percentage of invest and keep decisions at each ambiguity level ($N = 32$ per group in panels **a**–**c**; total $N = 96$). **b**, Participant-level significance breakdown across strategy groups. Stacked bar plot showing the number of participants in each strategy group whose individual test result is statistically significant ($P < 0.05$, dark blue) versus non-significant ($P \geq 0.05$, light blue) using χ^2 test. **c**, Decision time as a function of ambiguity level and investor type. Bars indicate mean ± standard error of the mean (SEM); dashed lines show fitted regression trends. Horizontal bars above the plots indicate significant group differences assessed using one-way ANOVA with posthoc *t*-tests and Bonferroni correction (0 Ambiguity: $F(2, 93) = 12.71$, $P < 0.0001$; *ideal* vs. *aggressive*: $T(31) = 3.24$, $P = 0.0019$, *aggressive* vs. *conservative*: $T(31) = -5.38$, $P < 0.0001$. 30% Ambiguity: $F(2, 93) = 4.49$, $P = 0.0138$; *aggressive* vs. *conservative*: $T(31) = -3.08$, $P = 0.0031$). **d**, Difference in pupil size between ambiguous and non-ambiguous trials over time for each investor type. Time 0 indicates decision start. Color-shaded regions denote SEM; gray bar on top indicate time intervals with significant effects evaluated using Wilcoxon signed-rank tests on sliding windows with false discovery rate (FDR) correction ($P < 0.05$). *N* denotes the number of participants per strategy group. Data in the black box are shown in box plots. The box plot with paired dots show each participant's mean pupil size change from baseline (%) measured in 0.5-1 s after decision onset under non-zero ambiguity and zero ambiguity conditions. Each dot represents one participant's averaged pupil response, and error bars indicate the within-participant SEM. Lines connect paired observations across conditions. Statistical significance was assessed using a paired *t*-test within each strategy group with Bonferroni correction (*ideal* : $T(31) = 2.62$, $P = 0.0400$; *aggressive*: $T(31) = 2.74$, $P = 0.0304$; *conservative*: $T(30) = 2.63$, $P = 0.0401$). Asterisks indicate significance as (*$P < 0.05$, * * $P < 0.01$, * * *$P < 0.001$).

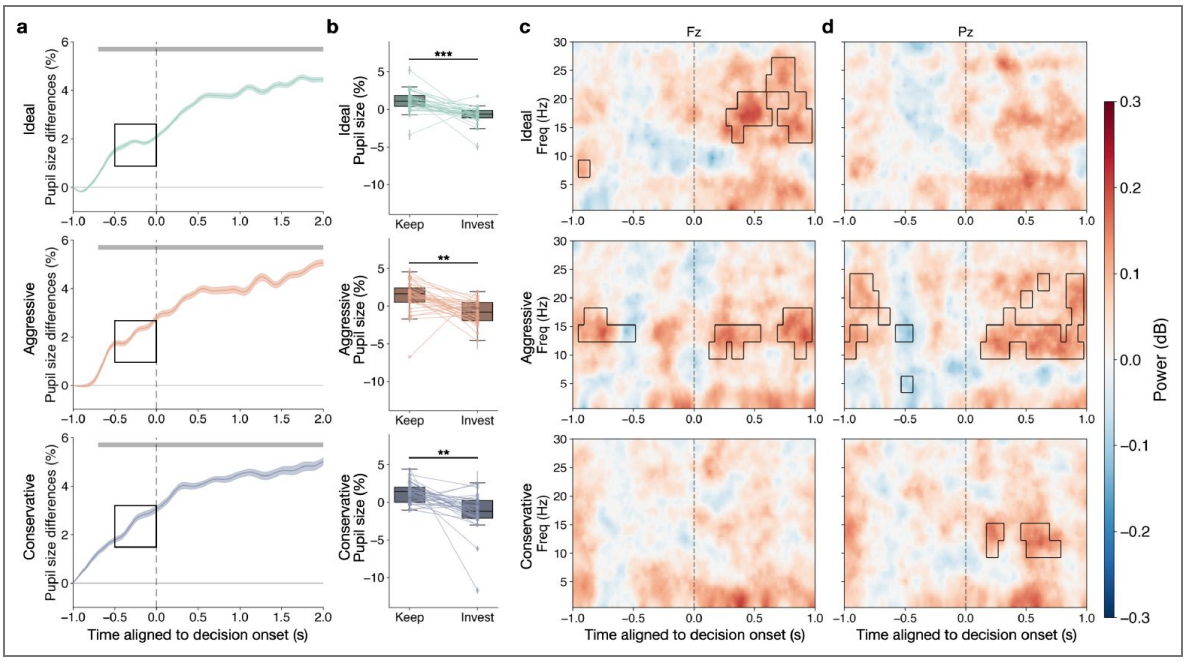

Fig. 3. Decision-dependent pupil and EEG signatures across decision strategies.

a, Time-resolved pupil size difference (*keep* minus *invest*) under ambiguous conditions for *ideal*, *aggressive*, and *conservative* investor groups. Shaded bands denote SEM across participants. Grey bar on top indicates time windows showing significant differences ($P < 0.05$), assessed using Wilcoxon signed-rank tests on sliding windows with false discovery rate (FDR) correction. **b**, Participant-level paired comparison of mean pupil size change from baseline (%) computed within the pre-decision interval highlighted by the black box in the left panels (0.5 s before decision onset). Each dot represents one participant (error bars: within-participant SEM), and lines connect paired observations. Group-level significance was assessed using paired *t*-tests with Bonferroni correction (*ideal* : $T(30) = 4.82$, $P = 0.0001$; *aggressive*: $T(30) = 3.92$, $P = 0.0014$; *conservative*: $T(30) = 3.96$, $P = 0.0013$). Asterisks denote significance (** $P < 0.01$, *** $P < 0.001$) and $N = 31$ for each strategy group in **a** and **b**. **c, d**, Time–frequency representations of EEG power differences (*keep* - *invest*) at frontal (Fz, **c**) and parietal (Pz, **d**) electrodes for each strategy group. Black outlines indicate time–frequency regions with significant differences ($P < 0.05$), evaluated using Wilcoxon signed-rank tests on sliding windows with FDR correction ($N = 25$ for *ideal* and *aggressive*; $N = 29$ for *aggressive*). Together, pupil and EEG results reveal distinct decision-dependent arousal and neural dynamics that vary systematically across *ideal*, *aggressive*, and *conservative* decision strategies.

Interestingly, pupil size differences between upcoming *keep*and *invest* choices were already present before the decision stimulus appeared. These differences indicate that arousal states predictive of choice emerged prior to the decision-making period (Fig. 3b). This anticipatory separation suggests that trial-to-trial variability in pupillinked arousal reflects more than reactive processing of decision evidence (56; 17). These pre-stimulus signatures align with evidence that pupil dilation can track endogenous belief states and predict upcoming decisions, consistent with models linking pupil dynamics to phasic locus coeruleus–norepinephrine (LC–NE) activity that regulates attentional gain and behavioral engagement (45; 12; 58). Together, the presence of *keep*–*invest* pupil differences before stimulus onset supports an interpretation in which a preparatory neuromodulatory state contributes to shaping decision outcomes, rather than arising solely as a consequence of deliberation.

2.3.2 Time–Frequency EEG Signatures of Strategy-Dependent Decision Process

EEG time–frequency analyses revealed reliable choice-dependent neural dynamics under ambiguity, with patterns that varied across decision strategies. We quantified spectrotemporal power differences between *keep*and *invest* decisions (keep – invest) at frontal (Fz, Fig. 3c) and parietal (Pz, Fig. 3d) electrodes, and identified significant time–frequency windows using sliding-window Wilcoxon signed-rank tests with false discovery rate (FDR) correction.

Ideal investors exhibited the most selective and temporally focused effects, dominated by post-decision frontal modulation. At the frontal channel, *ideal* investors showed a large, significant cluster spanning mid-to-high frequencies from about 0.3 s up to nearly 1.0 s after decision onset (Fig. 3c). This cluster reflected stronger betarange activity during *keep* relative to *invest*, suggesting enhanced recruitment of frontal decision-related oscillatory dynamics during the post-choice interval (5; 13; 24). In addition, a smaller pre-decision low-frequency cluster was observed around −0.9 s in the theta/alpha range, indicating that in *ideal* investors, choice-dependent neural differentiation may begin weakly prior to the decision point but becomes most pronounced after onset (38; 52). Notably, no comparably robust significant clusters emerged at the parietal channel for *ideal* investors (Fig. 3d), suggesting that their neural differentiation between decision types is expressed primarily through frontal beta-range dynamics.

Aggressive investors displayed the most widespread and temporally extended neural differentiation, with significant clusters present both before and after decision onset and across frontal and parietal electrodes. At the frontal channel, *aggressive* investors exhibited a prominent pre-decision cluster from approximately −1.0 to −0.5 s in the low-to-mid beta range (Fig. 3c,d), indicating anticipatory decision-specific modulation well before the decision time. Following onset, additional frontal clusters emerged in mid frequencies during the 0.1 −0.5 s window, along with a later post-decision cluster around 0.75–1.0s in beta range, reflecting sustained and multi-stage frontal engagement across the decision formation period (5; 13; 24). At the parietal channel, *aggressive* investors showed multiple significant pre-decision clusters spanning a broader frequency range, suggesting strong preparatory state differences that precede commitment. Post-decision, *aggressive* investors demonstrated a large sustained parietal cluster spanning roughly 0.1 −1.0 s in ∼10 −20 Hz. Together, these findings indicate that *aggressive* decision-making is characterized by distributed, anticipatory, and sustained oscillatory differentiation rather than a single focal post-onset signature.

Conservative investors showed comparatively sparse and localized effects. No significant clusters were observed at the frontal channel (Fig.3c), indicating minimal frontal differentiation between *keep* and *invest* decisions in this group. In contrast, at the parietal channel, *conservative* investors exhibited two discrete post-decision clusters in the alpha/low-beta range, occurring between about 0.2 0 −.4 s and 0.5 −0.8 s after stimulus onset (Fig.3d). This temporally constrained parietal modulation suggests that for *conservative* investors, decision differentiation is expressed primarily through posterior attentional or evidence-integration processes rather than frontal control-related dynamics, consistent with the role of parietal alpha/low-beta oscillations in controlled gating and suppression of competing representations during choice formation (16; 32).

Across strategy groups, these EEG signatures demonstrate substantial heterogeneity in the neural dynamics supporting the ambiguous decision process. *Ideal* investors show a strong and selective post-onset frontal beta-range signature, *aggressive* investors exhibit broad anticipatory and sustained differentiation across both frontal and parietal regions, and *conservative* investors show weaker effects that are localized to post-onset parietal alpha/low-beta dynamics. This pattern supports the interpretation that individual decision strategies correspond to distinct modes of neural engagement—ranging from focal frontal recruitment to distributed anticipatory oscillatory states—during strategy-dependent choice formation under ambiguity.

2.4 Behavior-Physiology Coupling Reveals Divergent Internal Models of Ambiguity

When making decision under ambiguity, decision strategies diverged sharply across investor types (F (2, 93) = 17.66, P < 0.0001). *Conservative* investors exhibited a significantly higher keep-to-invest ratio than both *ideal* and *aggressive* investors (Fig. 4a), indicating a strong bias toward the safe option under moderate ambiguity. In contrast, *aggressive* investors showed the lowest keep-to-invest ratio, reflecting a pronounced tendency to commit to the risky option even when outcome probabilities were partially unknown. *Ideal* investors fell between these two extremes. This behavioral separation under matched ambiguity provides direct evidence that individual decision styles express distinct asymmetric choice policies under ambiguity.

The behavioral asymmetry was accompanied by systematic differences in how participants internally represented the ambiguous portion of the lottery (Fig. 4b). Under 30% ambiguity, the inferred expected high-payoff probability k differed significantly across investor types (F (2, 93) = 8.93, P = 0.0003). *Conservative* investors assigned significantly lower values of k than both *ideal* and *aggressive* investors, indicating that they interpreted a larger fraction of the ambiguous probability mass as yielding the low-payoff outcome (mean SEM: *ideal,* k = 0.58 ± 0.12; *aggressive,* k = 0.63 ± 0.09; *conservative,* k = 0.45 ± 0.25). In contrast, *aggressive* investors assigned the highest values of k, reflecting a more optimistic internal model of ambiguous outcomes, with *ideal* investors again falling between the two extremes. These results demonstrate that divergent choice policies under ambiguity arise from distinct internal beliefs about the likely structure of unknown outcomes, rather than from uniform objective valuation alone.

Under a neutral valuation of ambiguity, we next examined whether these belief differences were also expressed in physiological arousal. We computed the time-resolved pupil response difference between ambiguous and non-ambiguous trials (Ambiguity *minus* No ambiguity), where ambiguity was defined using a fixed model that assumes an equal split of the ambiguous probability mass between high and low payoff outcomes. Under this neutral assumption, ambiguity elicited systematic deviations in pupil size relative to the no-ambiguity baseline (Fig. 4c, gray pupil sizes), indicating that pupil-linked arousal is modulated by ambiguity even when the objective ambiguity structure is held constant.

We then recomputed ambiguity using each participant's inferred subjective model, parameterized by the *expected k*. Strikingly, when pupil responses were expressed in this participant-specific belief space, the ambiguity-related pupil differences were no longer significant relative to zero (P > 0.05; Fig.4c, colored pupil sizes). This convergence indicates that the subjective internal model inferred from behavior provides a better account of physiological arousal than a neutral equal-split rule. Together, these results support a unified interpretation in which ambiguity-driven pupil dynamics track participants' internal beliefs about unknown outcomes: when ambiguity is quantified according to each individual's inferred *expected k*, pupil responses become indistinguishable from the no-ambiguity baseline, consistent with the view that the behavioral and physiological signatures reflect the same latent valuation model.

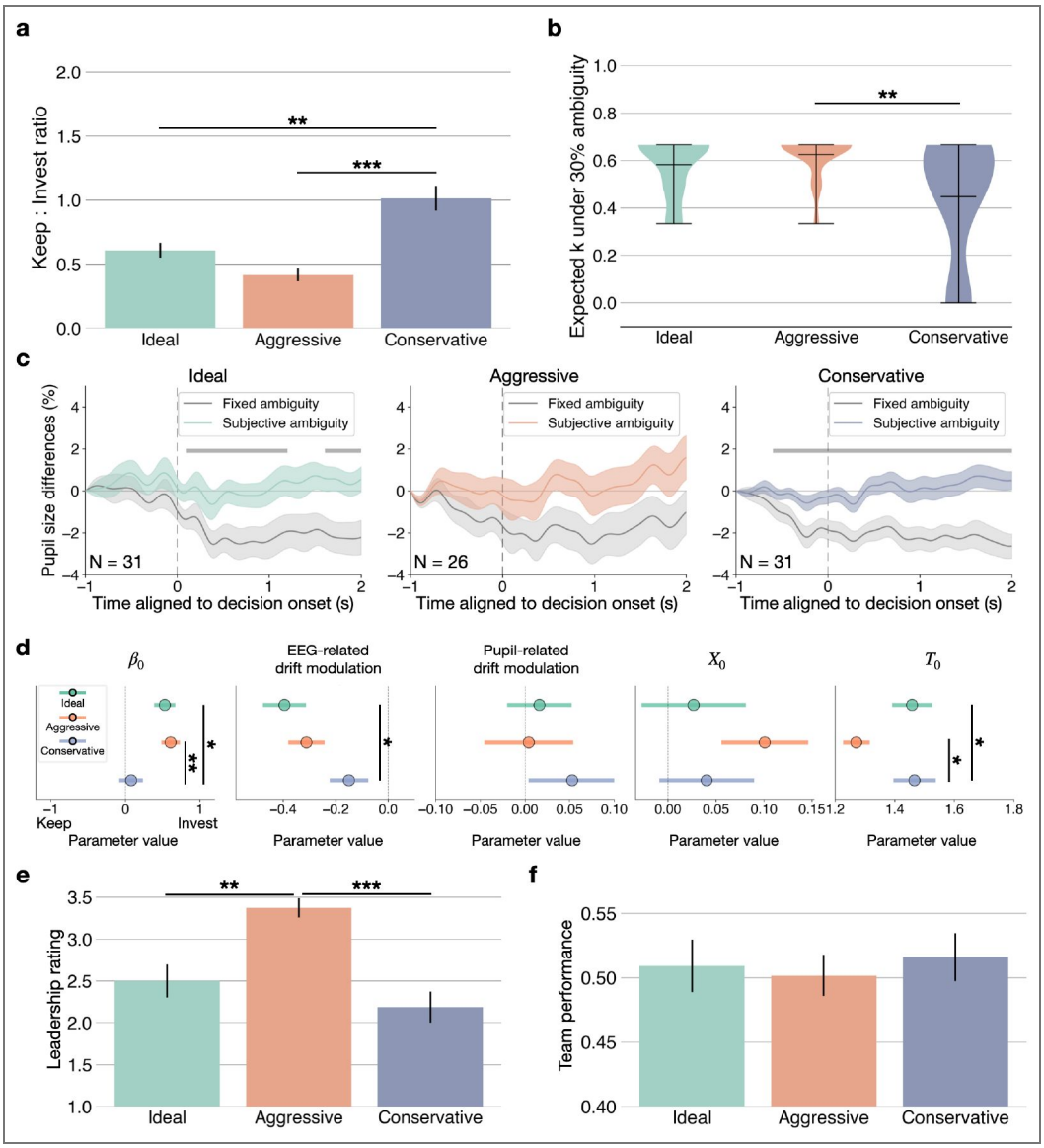

Fig. 4. Behavioral and pupil dynamics of divergent internal models under ambiguity.

a, Ratio of keep to invest decisions under ambiguity for *ideal*, *aggressive*, and *conservative* investors. *Conservative* investors exhibit a significantly higher keep-to-invest ratio than both *ideal* ($U = 257.50$, $P = 0.0026$) and *aggressive* investors ($U = 134.00$, $P < 0.0001$). **b**, Distribution of the inferred expected highpayoff probability k assigned to the ambiguous portion of the lottery for each investor type. *Conservative* investors assign lower values of k (*ideal* $U = 659.50$, $P = 0.1219$; *aggressive* $U = 735.00$, $P = 0.0025$), consistent with a pessimistic internal model of ambiguity relative to *ideal* and *aggressive* investors. Group differences in panels **a** and **b** were assessed using one-way ANOVA with post-hoc Mann-Whitney U test and Bonferroni correction (** $P < 0.01$, *** $P < 0.001$). **c**, Time-resolved pupil response difference between ambiguous and non-ambiguous trials (Ambiguity *minus* No ambiguity) for each investor type, comparing a fixed ambiguity model (equal split of high or low payoff) versus a subjective ambiguity model (each participant's inferred high-payoff belief *Expected k*). Shaded bands indicate SEM; gray bar on top denotes significant time windows of the fixed ambiguity model (Wilcoxon signed-rank test with sliding windows and FDR correction, $P < 0.05$). **d**, Strategy-dependent drift diffusion model parameters (mean ± SEM). Baseline drift rate (β_0), EEG-related drift modulation, pupil-related drift modulation, starting point bias (x_0), and non-decision time (t_0) are shown for the *ideal*, *aggressive*, and *conservative* groups. Baseline drift differed across strategies (Kruskal-Wallis, $H(79) = 13.46$, $P = 0.0012$). EEG-related drift modulation showed a marginal group effect ($H(79) = 5.53$, $P = 0.0629$). Pupilrelated drift modulation and Starting point bias (X_0) did not exhibit reliable group differences. Non-decision time differed across groups ($H(79) = 7.47$, $P = 0.0238$). $N = 25$ for *ideal* and *conservative*, $N = 29$ for *aggressive*. **e-f**, Leadership rating and team performance from collaborative task for each characteristic of participant. Oneway Analysis of Variance (ANOVA) with post-hoc pairwise comparisons with Tukey's HSD correction. Statistical significance is indicated as **$P < 0.01$, ***$P < 0.001$. N = 32 for each strategy group in a, b, d, and e.

2.5 Divergent Evidence Accumulation Processes Drive Behavioral Strategies

To characterize latent decision dynamics underlying *keep* versus *invest* choices across the three strategies, we fit drift diffusion models (DDMs) separately for each participant in the *ideal*, *aggressive*, and *conservative* groups (see *Drift Diffusion Modeling of Investment Decisions* in *Materials and Methods*). Evidence accumulation evolved between a lower bound corresponding to *keep* and an upper bound corresponding to *invest*. Participant's subjective rate of high-payoff, pupil-linked arousal, frontal–parietal EEG difference, and task context (trial progression and ambiguity) were incorporated as modulators of drift rate.

Significant strategy-dependent differences emerged in baseline drift rate (β_0; Fig. 4d, β_0). Post hoc Tukey HSD comparisons revealed that the *conservative* group exhibited significantly lower baseline drift relative to both the *aggressive* ($P = 0.0036$) and *ideal* ($P = 0.020$) groups, whereas the *aggressive* and *ideal* groups did not differ. These results indicate that *conservative* participants showed a reduced intrinsic tendency for evidence to accumulate toward investment, while *aggressive* and *ideal* participants exhibited comparable baseline accumulation biases toward *invest*.

Drift modulation by EEG difference showed a marginal overall group effect. Pairwise comparisons revealed weaker EEG-related drift modulation in the *conservative* group relative to the *ideal* group ($P = 0.035$). This pattern suggests that neural state fluctuations influenced evidence accumulation more strongly in *ideal* participants, whereas *conservative* participants exhibited attenuated sensitivity to EEG-derived signals. In contrast, drift modulation by pupil size did not differ significantly across strategies. This dissociation indicates that neural dynamics, rather than global arousal indexed by pupil size, primarily accounted for strategy-dependent differences in accumulation processes.

Starting point bias (X_0) did not exhibit reliable group differences, indicating that pre-decisional biases were comparable across the three groups. Interestingly, Nondecision time (t_0) differed significantly across groups. Tukey HSD comparisons revealed longer non-decision times in the *conservative* group relative to both the *aggressive* ($P = 0.0306$) and *ideal* ($P = 0.0398$) groups. This finding indicates that *conservative* participants required greater time for processes outside evidence accumulation than other two groups of participants.

Together, these results demonstrate that behavioral strategies are primarily distinguished by intrinsic evidence accumulation tendencies and differential neural modulation of drift. *Conservative* participants exhibited reduced baseline drift and weaker EEG-related drift modulation, consistent with diminished internal drive toward investment and attenuated neural sensitivity. *Aggressive* participants showed 14 baseline accumulation comparable to *ideal* participants but exhibited prolonged nondecision times, suggesting strategy-specific differences in peripheral processing rather than accumulation dynamics. Pupil-related drift modulation, subjective believe of high-payoff rate (K), and task related variables include ambiguity and trial index remained consistent across groups (Supplementary Information SFig. 2), indicating a shared computational mechanism for value integration and arousal-linked influences on decision formation.

2.6 Decision Strategies and Their Correlation with Leadership and Team Performance in Collaborative Task

Having established that decision strategies correspond to stable behavioral patterns, interpretable internal beliefs, and aligned physiological signatures, we next asked whether these individual differences extend to social behavior in collaborative settings. Before the Lottery Choice Task (LCT), participants completed a three-person collaborative spacecraft control task that required real-time coordination across distinct degrees of freedom under partial and complementary visual information (48). This phase provided an independent behavioral context in which leadership

tendencies and coordination styles could emerge prior to any individual ambiguity-based decisionmaking. This design enabled us to test whether the decision strategy reflects broader social traits rather than task-specific choice behavior.

Decision strategy was strongly associated with leadership behavior during collaboration. Participants classified into the three investor types received significantly different leadership ratings (F (2, 93) = 13.06, $p < 0.001$). *Aggressive* investors exhibited higher leadership scores than both *ideal* and *conservative* investors, whereas *conservative* investors received the lowest leadership ratings (Fig. 1b, *aggressive-ideal* : $P = 0.0013$; *aggressive-conservative*: $P < 0.0001$). This pattern suggests that individuals who assume greater leadership responsibility in team coordination are more likely to adopt risk-seeking strategies in subsequent individual value-based choices, whereas lower leadership engagement is associated with more conservative policies. These results align with prior work linking leadership, dominance, and risk tolerance in economic decision-making (20; 57).

In contrast, the decision strategy was not predictive of team performance. As shown in Fig. 1c, team performance did not significantly differ across investor types (F (2, 93) = 0.20, $P = 0.820$), and teams spanning the full performance range contained mixtures of *ideal*, *aggressive*, and *conservative* participants (Supplementary Information SFig. 1). Because performance in the collaborative task depends on the coordinated contributions of all three team members, and each potentially following a distinct decision strategy, individual investor type alone is insufficient to explain collective outcomes. This dissociation suggests that investor type captures individual leadership and risk preference, whereas team performance is dominated by interaction dynamics and coordination quality.

Together, these findings indicate that investor types reflect more than idiosyncratic ambiguity preferences: they are linked to stable social-role tendencies that generalize 15 to collaborative behavior. Leadership emerges as a key behavioral correlate of riskseeking strategies, while team performance remains a property of the group rather than any single decision style.

3 Discussion

Across a value-based decision-making task with controlled ambiguity, we identified three distinct decision styles, *ideal*, *aggressive*, and *conservative*, that differed systematically in behavior, internal belief about ambiguous outcomes, and physiological response. *Aggressive* investors showed a faster decision-making speed, a greater tendency to select the risky option, and higher subjective expectations of receiving the high payoff. *Conservative* investors exhibited the opposite pattern: slower and fewer investment decisions, reduced sensitivity to ambiguity, and markedly lower subjective estimates of high-payoff probability. *Ideal* investors occupied an intermediate regime, showing balanced evaluation of keep and invest options and robust neural differentiation between decision types. Physiological signals, including pupil-linked arousal and EEG dynamics, further distinguished these groups and revealed that decision style is expressed not only in overt behavior but also in the underlying arousal and control processes engaged during choice. Together, these findings show that ambiguity does not evoke a uniform behavioral or physiological response across participants with different decision-making styles; instead, individuals rely on distinct internal models and computational strategies when forming decisions under ambiguity.

Classical accounts of ambiguity aversion often assume a single, population-wide tendency to avoid options with unknown probabilities (18; 14; 11). Our findings challenge this view. Individuals construct markedly different internal beliefs about ambiguous outcomes, and these beliefs shape both behavior and physiology. *Ideal*, *aggressive*, and *conservative* investors did not simply differ in how often they chose the risky option; they differed in their subjective estimates of the ambiguous probability mass, in their pupil-linked arousal responses, and in their neural engagement during the decision process. *Aggressive* investors assigned slightly higher subjective probability to receiving the high payoff than *ideal* investors, whereas *conservative* investors assigned much lower values, reflecting a more pessimistic internal model of ambiguity. These belief differences were mirrored in physiology, where *conservative* investors showed weaker pupil modulation by

ambiguity and distinct EEG patterns of keep and invest. Taken together, these results show that ambiguity aversion is not a uniform psychological bias, but a set of heterogeneous belief-driven strategies that shape how ambiguity is represented and acted upon.

Across investor types, behavioral patterns aligned closely with participants' internal beliefs about ambiguous outcomes (21). *Conservative* investors showed the highest keep-to-invest ratios under ambiguity and also assigned the lowest subjective k values, indicating that they not only acted cautiously but believed that high-payoff outcomes were unlikely. *Aggressive* investors displayed the opposite pattern, where they had the lowest keep-to-invest ratios and assigned the highest subjective k values. These differences suggest that *aggressive* investors held a more optimistic internal model of ambiguous outcomes than *conservative* investors. *Ideal* investors consistently fell between these two extremes. This tight correspondence between belief and behavior shows that participants' choices were not random or inconsistent (29). Instead, they reflected stable internal valuation models that shaped how each group interpreted and acted in the face of ambiguity.

These belief–behavior links were mirrored in the physiological signatures of decision making. Under a neutral expected-value assumption, where the ambiguous probability mass was treated as evenly split between high and low pay-offs, pupil responses are significantly different across investor types when making ideal investments (Fig. 4b). This indicated that groups engaged different levels of arousal even when applying the same objective valuation rule (7; 60; 8). However, these differences disappeared once the expected value was recomputed using each participant's own subjective *k* (Fig. 4c). When ideal decisions were evaluated under each individual's internal belief model, pupil responses no longer differed across groups. This shift demonstrates that pupillinked arousal does not reflect a fixed reaction to ambiguity across groups. Instead, it tracks the subjective value each participant assigns to the ambiguous portion, aligning directly with their internal beliefs and behavioral tendencies. Physiological responses, therefore, provide convergent evidence that ambiguity processing is belief-driven, not solely stimulus-driven.

Neural dynamics further revealed that each investment style engages a distinct computational pathway when resolving ambiguity. *Ideal* investors showed early enhancements in delta and theta power, along with broader frontoparietal recruitment, consistent with rapid evaluation of competing options and early engagement of control systems (61; 43; 55). In contrast, *aggressive* and *conservative* investors showed limited early low-frequency activity and instead differentiated keep and invest decisions through posterior alpha modulation, reflecting shifts in cortical excitability and attentional allocation (51; 59). *Aggressive* investors additionally showed a late alpha signature when choosing against their default tendency, suggesting engagement of conflict-monitoring or effortful control processes (41; 42). *Conservative* investors, by comparison, displayed generally muted low-frequency responses, consistent with a less dynamically engaged decision regime. Together, these patterns indicate that individuals do not simply vary in their decision thresholds; they draw on qualitatively different neural mechanisms when forming decisions under ambiguity.

Across these modalities, a unified model of ambiguity processing emerges. *Ideal* investors combine balanced subjective beliefs with early control-related neural engagement, enabling them to evaluate ambiguous options through an integrated valuation process. *Aggressive* investors display the opposite pattern: they hold more optimistic beliefs about ambiguous outcomes and rely on heightened cortical excitability to commit rapidly to the risky option, engaging additional control signals only when acting against their default tendency (41; 42). *Conservative* investors adopt a pessimistic interpretation of ambiguity and operate in a low-engagement neural regime, with weaker arousal responses and muted low-frequency signaling that track their reluctance to invest. Together, these profiles suggest that individuals do not differ merely in their preferences under ambiguity. Different groups differ in the internal models they construct, the arousal systems they recruit, and the neural computations they engage when forming decisions. Ambiguity processing, therefore, reflects distinct belief-driven pathways rather than a single canonical mechanism.

Our findings also refine several longstanding theoretical accounts of decision making under ambiguity. Classical ambiguity frameworks, beginning with Ellsberg (18), assume a uniform population-level aversion to unknown probabilities, but our results show that this aggregate pattern masks structured heterogeneity in how individuals internally represent ambiguity (Fig. 2a). Our data demonstrate that internal beliefs about receiving high payoffs are reflected not only in choice patterns but also in arousal signatures and neural dynamics. Work on LC–NE–mediated arousal has highlighted pupil dilation as a marker of ambiguity or cognitive demand (62; 45; 23), but our results show that pupil responses also track subjective valuation rather than just ambiguity. In decision neuroscience, theta, alpha, and delta rhythms are often interpreted as generic markers of control, attention, or valuation (25; 63; 10; 61). We show that participants' expressions differ systematically across decision styles, revealing distinct computational modes rather than simple increases or decreases in activation. Together, these links to prior theory demonstrate that ambiguity is not a single psychological construct but a multi-level phenomenon shaped by individual beliefs, physiological engagement, and neural computation.

Importantly, our results also indicate that decision-making under ambiguity is shaped not only by stimulus-evoked valuation processes but also by pre-stimulus internal states. In pupillometry, all three strategy groups exhibited reliable *keep - invest* differences prior to stimulus onset, suggesting that endogenous arousal fluctuations can predict forthcoming choice (56; 17). EEG provided convergent, but strategydependent, evidence for such anticipatory differentiation. *Aggressive* investors showed the clearest pre-stimuli differences between *keep* versus *invest* decisions, indicating that neural states predictive of choice can emerge well before the decision period (38; 52). *Ideal* investors exhibited only a weaker pre-decision effect, and *conservative* investors showed no significant pre-decision EEG clusters. These results suggest that anticipatory neural differentiation is not uniformly expressed across participants with strategies. One possibility is that participants enter each trial with fluctuating internal states, such as expectation, decision bias, or action preparedness, that bias the probability of selecting *keep* versus *invest*. Alternatively, these pre-stimulus physiological differences may reflect carryover from the previous trial, producing lingering engagement or subjective certainty that biases the subsequent decision. Together, these findings suggest that ambiguity processing unfolds within a dynamically varying internal context, in which endogenous arousal and preparatory neural states shape decision outcomes even before evidence is evaluated.

Several limitations of this study also point to clear directions for future work. First, our laboratory task used fixed ambiguity levels (30% and 60%), which enabled precise inference of internal belief models but may not capture the full complexity of real-world ambiguity. Extending this framework to naturalistic settings, such as real-time financial decision-making, including stock trading or shopping decisions, will be an important next step. Second, although pupil size reliably indexed arousal and tracked subjective valuation, it is not a process-pure marker of LC-NE activity. Future studies combining pupillometry with higher-resolution methods, such as EEG–fMRI, could more directly link arousal dynamics to neuromodulatory mechanisms. Third, the limited spatial resolution of EEG constrains source-level interpretation, motivating multimodal approaches to better resolve the neural circuits underlying belief-driven ambiguity processing. More broadly, our results open avenues for linking internal belief models to personality, risk preference, and psychiatric phenotypes, and for designing adaptive decision-support and human–AI systems that respond to latent beliefs rather than observable choices alone.

4 Materials and Methods

4.1 Participants

We recruited 57 healthy adult participants (mean age 23.68 ± 3.32 years; 25 female), all with normal or corrected-to-normal vision. Each individual completed one to three experimental sessions. For data analysis, each session was treated as an independent participant, yielding a total of 108 sessions. Data from 7 sessions were excluded due to incompletion, and 5 additional sessions were excluded due to low task engagement (selecting only one option across trials). EEG data from

17 sessions were discarded due to poor signal quality, and pupil size data from 1 sessions were excluded due to failed eye-tracker calibration. The final dataset included behavioral data from 96 sessions, pupil data from 95 sessions, and EEG data from 79 sessions. All procedures were approved by the Institutional Review Board at Columbia University, and written informed consent was obtained from all participants prior to each session.

4.2 Experimental Design

Each participant completed the Lottery Choice Task (LCT) following a collaborative decision-making task, the Apollo Distributed Control Tast, and an associated questionnaire (46; 47; 48). The LCT was designed to assess individual risk preferences under varying levels of ambiguity and under time pressure. Participants were instructed to maximize their total score, which was partially linked to monetary rewards.

Each trial began with a 1 second fixation period, followed by a decision phase lasting up to 5 seconds. Participants were randomly assigned an initial point endowment and asked to either keep the amount or invest it for a probabilistic return. The repayment probability was displayed using a pie chart representing either (1) a social condition, featuring a human face labeled as a prior participant, or (2) a non-social condition, featuring a roulette image representing a computer-generated gamble. There was no correlation between stimulus type and the probability of return.

After the decision was made and confirmed, a 2 second reviewing period began. During this phase, a ball rotated around the outer pie chart and stopped to reveal the investment outcome, indicated both by the ball's final color and an outcome message displayed above the pie chart. If participants failed to respond in time, the trial was flagged as skipped and repeated later.

The task manipulated three levels of ambiguity:

- **No ambiguity:**all outcome probabilities and amounts were fully known.
- **Moderate ambiguity:** 30% of the pie chart was hidden.
- **High ambiguity:** 60% of the pie chart was hidden.

In ambiguous trials, the hidden region could belong entirely or partially to either payoff region, creating uncertainty about both the likelihood and the value of the outcome.

Each session contained 132 valid trials. Trials in which participants failed to respond within the 5 s decision window were repeated later at a random position in the session. Therefore, the total number of trials presented could exceed 132, but 132 trials were retained for analysis. The task was implemented in an immersive virtual reality environment. Participants interacted with the task using a head-mounted display (HTC VIVE Pro Eye, 1440 × 1600 pixels per eye, refresh rate of 90 Hz) and handheld controllers (HTC VIVE Controller) while seated in a quiet, EEG-shielded chamber. Behavioral responses, eye tracking (pupil size), and EEG signals were recorded continuously throughout the task.

The virtual interface displayed two side-by-side panels per trial. One panel showed a full pie displaying the initial endowment. Another panel displayed the stimulus (face or roulette) above a pie chart indicating repayment probabilities and amounts. Each segment of the pie showed a numerical value representing the potential return and a corresponding percentage around the outer edge. In ambiguous conditions, a portion of the pie was shaded without a numerical label, and only the percentage of the unknown portion was displayed. Participants confirmed their selection by clicking a "submit" button located between the two panels after each trial. The reviewing period began immediately after submission.

4.3 Behavioral Data and Participants Classification

To understand how participants made investment decisions under varying conditions, we analyzed the frequency of "keep" versus "invest" responses across different levels of ambiguity and stimulus type. We then used physiological signals, combined with game context variables, to build predictive models of individual investment decisions.

Each investment trial was associated with an expected value (EV), computed as:

$$EV = P_{\text{high}} \cdot R_{\text{high}} + P_{\text{low}} \cdot R_{\text{low}}\,, \tag{1}$$

where P denotes the probability and R the corresponding return amount. For ambiguous trials, EV was evaluated using the actual underlying probabilities excluding the ambiguous portion.

We categorized each decision into one of three types based on the comparison between the EV and the initial endowment:

- **Ideal decision:** Participant chose to invest when *EV* > initial, or to keep when *EV* < initial.
- **Aggressive decision:** Participant chose to invest even when *EV* < initial.
- **Conservative decision:** Participant chose to keep even when *EV* > initial.

For each participant, we computed the proportion of decisions falling into each category. Participants were then ranked by the proportion of ideal, aggressive, and conservative decisions. The top one-third were labeled as *Ideal investors*. Among the remaining two-thirds, the top half (one-third overall) were labeled as *Conservative investors*, based on their conservative decision rate. The remaining participants were categorized as *Aggressive investors*.

This classification yielded three mutually exclusive behavioral profiles, which served as the foundation for subsequent physiological and behavioral analyses and predictive modeling.

4.4 Pupil Data Acquisition and Preprocessing

Pupil data were recorded using the integrated eye tracker on the HTC VIVE Pro Eye virtual reality headset, operating at a sampling rate of 120 Hz with a trackable field of view of 110°. The system recorded pupil size, gaze position, gaze direction, and eye openness continuously throughout the task.

Pupil size preprocessing involved blink and artifact detection, followed by linear interpolation over missing values. The interpolated signal was then filtered using a 4th-order Butterworth low-pass filter with a cutoff frequency of 2 Hz. Pupil diameter was averaged across the two eyes to obtain a single time series per trial.

Pupil size was normalized for each trial using the formula:

$$x_{\text{norm}} = \frac{x - \text{base}}{\text{base}}, \tag{2}$$

where x is the pupil size time series and base is the baseline pupil size measured during the 1-second fixation period preceding the decision phase. We analyzed pupil dynamics during the 0–2 second window following stimulus onset, corresponding to the decision-making period. Trials with decision times shorter than 2 seconds were excluded from pupil analysis to ensure consistent temporal alignment across trials.

To isolate decision-related pupil dynamics, we removed the transient pupil response evoked by stimulus luminance changes using a generalized linear model (GLM). For each participant, we modeled the luminance-evoked pupil response as a step-like impulse response using a finite impulse response (FIR) basis and fit the model only to the early post-stimulus window (the first 1 second), when luminance-driven effects dominate. A ridge-regularized regression was used to estimate a participant-specific luminance response kernel shared across trials. The fitted luminance component was then extrapolated to the full trial, held constant after the early window to avoid removing later decision-related dynamics, and smoothly blended at the boundary. This estimated luminance contribution was subtracted from the raw pupil signal, yielding a luminance-corrected pupil trace used for all subsequent analyses.

4.5 EEG Data Acquisition and Analysis

EEG data were recorded using the B-Alert X24 system (Advanced Brain Monitoring), which includes 20 electrodes placed according to the international 10–20 system and sampled at 256 Hz. The system used two mastoid electrodes for referencing. Participants completed the task while seated in an EEG-shielded booth to minimize environmental artifacts.

EEG preprocessing was performed using custom Python scripts. First, bad channels were detected and excluded based on signal amplitude thresholds using PyPREP (2). The removed channels are interpolated using MNE (28). The data were then bandpass-filtered between 0.5 and 30 Hz using a zero-phase Butterworth filter. Independent component analysis (ICA) was applied to identify and remove components related to ocular and muscular artifacts. All EEG traces were visually inspected post-ICA to confirm artifact removal.

Continuous EEG data were epoched around stimulus onset, spanning a window from 0.25 to 1 seconds. The −0.25 *s* preceding stimulus onset served as the baseline for baseline correction and was excluded from subsequent analyses. All analyses focused on the post-stimulus interval from 0 to 1 second. Participants with fewer than 5 valid trials per condition were excluded from EEG analysis. Following baseline correction using the pre-stimulus window (−0.25 to 0 s), we cropped epochs to the 0–1 second post-stimulus interval.

Frequency-domain analysis targeted the delta (0.5–4 Hz), theta (4–8 Hz), and alpha (8–13 Hz) bands, which are strongly implicated in cognitive control and value-based decision making (39; 53).

4.6 Drift Diffusion Modeling of Investment Decisions

To quantify latent cognitive processes underlying *keep* and *invest* decisions (49), we employed drift diffusion modeling (DDM) using the PyDDM framework (54). Choices were coded as keep = 0 and invest = 1, corresponding to the lower and upper absorbing decision bounds, respectively. Models were fit separately for each participant using trial-wise decision times and binary choices.

Trial-wise EEG features were computed using Morlet wavelet time-frequency decomposition implemented in MNE (28). Frequencies from 0.5 to 30 Hz (60 linearly spaced bins) were used with the number of cycles set to half the frequency. Power estimates were baseline-normalized using a log-ratio transform relative to a pre-stimulus baseline window of [−0.7, −0.5] s. For each trial, baseline-normalized power was averaged within the 8-13 Hz band and a 0-0.5 s post stimuli onset time window at channels Fz and Pz. The EEG regressor used in the model was defined as the difference between these two channels,

$$\mathrm{EE}_{\mathrm{G}_{\mathrm{diff}}} = \mathrm{EEG}_{P_F} - \mathrm{EEG}_{P_P},$$

capturing trial-wise frontal-parietal spectral imbalance.

The subjective value term *K* was assigned according to each participant's internal believe of the high-payoff rate under ambiguity, yielding a participant-specific estimate of expected value under uncertainty. Trial-wise pupil and EEG covariates were z-score normalized within each participant to remove between-subject scaling differences.

Evidence accumulation was modeled as a stochastic diffusion process evolving between two fixed absorbing bounds. The diffusion noise was fixed to 1.0 and the boundary separation was fixed to 1.8 across participants. The model estimated a starting point parameter (x_0), representing initial decision bias toward either choice, and a non-decision time parameter (t_0), capturing sensory encoding and motor execution processes outside the accumulation stage.

The drift rate was modeled as a linear function of trial-level cognitive and physiological covariates:

$$v = \beta_0 + b_k \cdot K + b_{\mathrm{pupil}} \cdot \mathrm{Pupil} + b_{\mathrm{eeg}} \cdot \mathrm{EEG} + b_{\mathrm{task}} \cdot (\mathrm{TrialID} + \mathrm{Ambiguity}), \quad (3)$$

where β_0 denotes the baseline drift rate, *K* denotes subjective value of getting highpayoff, Pupil denotes the trial-wise pupil scalar, EEG denotes the frontal-parietal 13-15 Hz EEG difference in 0.1 to 0.4 s post stimuli onset, and TrialID + Ambiguity encodes the trial index

and ambiguity level of the trial. Positive drift values indicate faster accumulation toward the *invest* decision.

Model parameters were estimated independently for each participant using maximum-likelihood estimation with the BADS optimizer implemented in PyDDM. Parameter bounds were constrained to ensure stable optimization: β_0, b_k, b_{pupil}, b_{eeg}, b_{task}, [−1, 1], $x_0 \in [1, 1]$, bound $\in [0, 2]$, and $t_0 \in [0, 2]$. This procedure yielded participant-specific estimates of baseline accumulation tendencies, sensitivity to subjective value, modulation by pupil-linked arousal, EEG-derived neural state, task related effects, starting bias, bound, and non-decision time. The model fit quality measured by negative log likelihood is shown in Supplementary Information SFig. 3.

4.7 Statistical Analyses

4.7.1 Behavioral

To verify that differences in investment decision patterns across ambiguity levels and stimulus types are statistically significant, we used Cochran–Mantel–Haenszel (CMH) tests to evaluate stratified contingency tables, controlling for participant-level variation. Reaction times were analyzed using a linear mixed-effects model with stimulus type as a fixed effect and a random intercept for each participant:

$$\text{DecisionTime} \sim \text{Stimuli} + (1|\text{Participant}). \quad (4)$$

For group-level comparisons related to leadership scores and team performance (derived from the preceding Apollo Distributed Control Task), we applied one-way ANOVA with Bonferroni correction for multiple comparisons.

4.7.2 Physiological

Pupil size time-resolved condition effects were evaluated using sliding-window tests across the pupil time course (0.4 s window; 0.2 s step). For within-participant comparisons (e.g., *keep* vs. *invest* within an investor type), we used Wilcoxon signed-rank tests on the window-averaged pupil values. For between-group comparisons across investor types (*ideal*, *aggressive*, and *conservative*) at each window, we used Kruskal–Wallis tests. For each analysis, we controlled multiple comparisons across windows using FDR correction, and significant time intervals were reported/visualized as contiguous FDR-significant windows.

Statistical comparisons between *keep*and *invest* decisions' EEG were performed using paired tests across participants in a sliding-window manner over time and frequency. Specifically, power values were averaged within overlapping temporal windows (0.1 s windows with 0.05 s steps) and narrow frequency bands (3 Hz width). Pairedsample tests were computed for each time–frequency bin, and false discovery rate (FDR) correction was applied across all bins to control for multiple comparisons.

Data availability

All deidentified behavioral, electroencephalogram (EEG), and pupil data have been deposited at *https://osf.io/yz8ef* and are publicly available. The code for the analyses presented in this paper is openly accessible at *https://github.com/YinuoQ/LCT_ambiguity_expection*.

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Additional files

Supplementary file 1.

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Yinuo Qin, Nuttida Rungratsameetaweemana, Nina Lauharatanahirun, Paul Sajda (2021) Pupil And Neural Dynamics Reveal Belief-Dependent Decision Making Under Ambiguity. OSF. ID yz8ef https://osf.io/yz8ef

Peer reviews

Reviewer #1 (Public review):

Summary:

The manuscript investigates value-based decision-making under risk and ambiguity using a combination of behavioral, pupillometric, and EEG data. Participants are stratified into three "decision styles" (ideal, aggressive, conservative) based on how their choices under known risk align with expected-value optimality. The central claim is that ambiguity aversion is not a uniform bias but reflects heterogeneous internal belief models, and that physiology tracks subjective belief rather than objective task structure. While this is an interesting conceptual question, the evidence is underwhelming given that differences between groups are not tested statistically (but just described), there are clear problems with how the computational models are implemented, and there are serious issues with sampling of participants.

Strengths:

The multimodal design (behavior, pupillometry, EEG) and the attempt to link a latent belief parameter to physiological signatures address a question of clear interest.

Weaknesses:

Framing and motivation

(1) The framing conflates two questions that appear distinct. The motivation centers on "ambiguity aversion," but the study's actual aim - how individuals internally represent ambiguous outcomes - seems like a different question. The relationship between these two framings needs to be made explicit, because as written the motivating phenomenon and the studied phenomenon are not obviously the same thing.

(2) Several of the contrasts the paper sets up against prior literature read as strawmen. The claim that ambiguity aversion is treated as "a single bias or fixed trait that applies uniformly" is presented as the view being overturned, but it is not clear this is a position the field actually holds - it reads as a strawman. Relatedly, the central objective-versus-subjective valuation distinction that the results are built around also reads as a strawman dichotomy rather than a genuine competing account.

(3) The motivation for the physiological measures is overly broad. The statement linking EEG to control, attention, valuation, uncertainty, conflict, effort, and engagement is so general as to be uninformative - EEG signals have been linked to essentially everything, so this does not constrain the hypotheses or predictions. A more specific, falsifiable rationale is needed.

Design, sample, and grouping.

(4) The inclusion of the collaborative spacecraft/Apollo task is unclear. It is not explained why this task is included, and its role relative to the core ambiguity question needs justification (this also bears on the leadership analyses; see below).

(5) The participant numbers do not add up and must be reconciled. The text reports 57 participants, yet the analyses describe three groups of roughly 32 + 32 + 31. The relationship

between participants, sessions, and group n's needs to be stated clearly and consistently, because at present the sample description is internally contradictory.

(6) The rationale for categorizing participants into three discrete groups is not established, and the approach is statistically questionable. Decision tendency appears to be a continuous variable; dichotomizing/trichotomizing a continuous measure is generally discouraged and can manufacture or distort group differences. The authors should justify why discrete groups are needed at all, and ideally show whether there are genuine group differences (e.g., evidence of discontinuity/clustering) rather than an arbitrary split of a continuum.

Statistics

(7) Key claims about how ambiguity affects groups differently are made without the appropriate test. To support a claim that the effect of ambiguity differs across groups, the interaction (group × ambiguity) must be shown - group-wise effects reported separately are not sufficient. This is really a key limitation of the current work.

(8) The methods mentioned that some participants performed multiple sessions, but their data were treated as if coming from separate participants. This is incorrect for several reasons, particularly given the focus on individual differences.

Belief parameter and terminology

(9) The term "ideal" is not justified. It is unclear why this group is labelled "ideal" - are they Bayes-optimal, or optimal in some defined sense? If the label implies normativity, that needs to be demonstrated; otherwise it should be renamed.

Drift-diffusion modelling

(10) The boundary parameter is fixed (a detail which is hidden in the methods), but this is highly problematic. By enforcing the same boundary value for all participants, the model is forced to capture any variation as drift rate effects. As such, all conclusions about drift rate are not interpretable as they might reflect boundary effects in disguise.

(11) The DDMs are fit separately per group of participants, which again precludes testing interactions. As with the behavioral analyses, fitting separate models means group differences cannot be properly compared within a single statistical framework, and interactions cannot be assessed. The paper does mention some comparison between groups, but comparing DDM parameter estimates across separately fit models is not valid.

(12) Overall, the DDM is very complex, and the manuscript does not yet provide enough validation to make the model trustworthy. Given the number of trial-wise covariates entering the drift rate and the per-participant fitting, stronger evidence that the model is identifiable and that its parameters are recoverable/reliable is needed before the conclusions drawn from it can be accepted.

Methods - EEG and analysis details

(13) The high-pass filter setting appears very aggressive. The authors should confirm whether this risks removing genuine low-frequency signal of interest, particularly given that delta-band effects are later interpreted.

(14) There is an apparent inconsistency in the epoching/time-locking. The time-frequency analysis appears to be computed on choice-locked data, yet elsewhere the epochs are described as stimulus-locked. This needs to be clarified and made consistent, as it affects interpretation of the pre- versus post-decision EEG clusters.

(15) The mixed-effects modelling appears to omit random slopes. The authors should justify the random-effects structure (e.g., why only random intercepts), as this affects the validity of the inference.

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Reviewer #2 (Public review):

Summary:

The manuscript by Qin and colleagues entitled "Pupil and Neural Dynamics Reveal Belief-Dependent Decision Making Under Ambiguity" examines decision-making under risk and ambiguity using pupillometry and EEG. The study employs a lottery choice task with three levels of ambiguity (zero, low, high). Participants were classified into three groups based on their choice behavior in a condition with risk and no ambiguity: ideal (choosing in line with objective expected values), aggressive (preference for investments), and conservative (preference against investments). The authors then compared behavior, pupil, and EEG results across these groups. The study concludes that individual beliefs about ambiguity are reflected in different behavioral strategies and neural correlates.

Strengths:

The combination of behavior, computational modeling, pupillometry, and EEG.

Weaknesses:

(1) It is unclear whether group definition is theoretically justified.

One general concern is that the strategy to form three distinct groups is not clearly motivated. The authors created the three groups, "aggressive", "ideal", and "conservative", based on the zero-ambiguity trials. However, as the authors state: "Ambiguity differs fundamentally from risk at both the physiological level (34; 6) and the behavioral level" (page 4). Under this assumption, it is questionable whether forming groups based on risk preferences is a useful strategy for studying ambiguity. What do we learn about ambiguity processing when group differences are primarily based on risk preferences? Might the present results partly be driven by risk preferences rather than ambiguity preferences? I recommend the following two points: (a) Clearly justify the reasoning behind the group approach; (b) Add an additional continuous analysis approach indicating whether the key results hold independent of the group definition based on risky decision-making.

(2) k-parameter.

The authors use the k-parameter that infers the expected high-payoff probability (e.g., page 11). On page 22, this is explained as: "the subjective value term K was assigned according to each participant's internal belief of the high-payoff rate under ambiguity, yielding a participant-specific estimate of expected value under uncertainty." I hope I have not missed anything, but I neither understood the role of this parameter nor how it was computed.

(3) How were individual beliefs and models computed?

A related but more general point is that it remained unclear how the authors computed internal beliefs and internal models in the study. The study contains many statements suggesting that the authors measured internal beliefs. For example:

a) Abstract: "We show that individuals adopt distinct decision strategies that reflect different internal beliefs about unknown outcomes."

b) Page 3: "We then inferred subjective belief parameters that captured how individuals internally interpreted the ambiguous probability mass and examined how these beliefs related to choice behavior, arousal dynamics, and neural activity."

c) Page 16: "Together, these findings show that ambiguity does not evoke a uniform behavioral or physiological response across participants with different decision-making styles; instead, individuals rely on distinct internal models and computational strategies when forming decisions under ambiguity."

d) Page 16: "Taken together, these results show that ambiguity aversion is not a uniform psychological bias, but a set of heterogeneous belief-driven strategies that shape how ambiguity is represented and acted upon."

e) Page 18: "Ambiguity processing, therefore, reflects distinct belief-driven pathways rather than a single canonical mechanism."

Based on the present data, analyses, and results, I don't think that the authors can draw these conclusions. Which analyses in the manuscript identify these internal beliefs, models, or strategies? How can we dissociate a unified strategy from a heterogeneous set of strategies based on the present results? My feeling is that the k-parameter might be related to this, but as explained above, I did not understand how it was computed and what it is supposed to reflect. The DDM analyses might also be targeted at this. However, it remains elusive how the DDM captures internal beliefs about ambiguity itself. My recommendation is that the authors more clearly explain (a) why the DDM is a useful model to study ambiguity, (b) what the different parameters exactly reflect about ambiguity processing, and (c) how the DDM captures internal beliefs and distinct belief-driven strategies in this context.

(4) Statistical tests.

4.1. Figure 2B: The authors summarize the number of participants with significant effects of ambiguity on choice behavior for each group. I recommend a statistical test at the second level that properly assesses the effects of ambiguity and group within a common statistical model. In my opinion, it is not enough to simply count the number of significant tests (from the first level) for each group.

4.2. Figure 2C: For the analysis of response times, the authors might want to consider reporting the main effects of group and ambiguity.

4.3. Figure 2D: The text on page 8 states that Figure 2D indicates that "aggressive investors showed no significant pupil modulation by ambiguity...". However, the figure and its caption indicate significant differences between ambiguous and non-ambiguous trials across all groups. Moreover, if the authors want to compare the groups, it is necessary to compare the groups to each other; a test against zero within each group would not be enough to demonstrate any group differences. In my mind, this would also be important for analyses in Figure 3C and D.

4.4. Strictly speaking, for the statistical tests, it would be necessary to take into account that participants completed multiple sessions (within-subject variance is different from between-subject variance). Currently, each session is treated independently (page 19: "Each individual completed one to three experimental sessions. For data analysis, each session was treated as an independent participant, yielding a total of 108 sessions.")

(5) Necessary quality control for pupillometry and EEG data.

The task was performed in a virtual reality environment with a head-mounted display. The task was not isoluminant, and, to the best of my knowledge, participants were not instructed to avoid eye movements. The authors applied a GLM to control for luminance effects in the

pupil data. For EEG, they used ICA to remove ocular and muscular artifacts. While these methods are established, they are usually applied to more controlled paradigms optimized for EEG and pupillometry. To demonstrate high data quality despite these issues, it is necessary to present quality-control analyses. Can the authors please indicate how many blinks had to be removed from the data? Could the authors please indicate how many blinks were removed from the data? Can the authors please show trial-level data (after preprocessing) for a few subjects?

(6) Quality control for the DDM.

The manuscript lacks systematic posterior predictive checks and parameter recovery for the DDM results. It is important to validate that the model accurately captures the data. Currently, we only see the model parameters, but it remains unclear whether the model performs well on the current data set. Moreover, if the authors aimed to test different strategies using the DDM, it might be useful to perform systematic model comparison.

(7) Implications of the second experiment with collaborative task remain unclear.

To me, the link between the main study and the second experiment on leadership and team performance is not obvious. In my opinion, this topic is beyond the scope of the present paper. Linking the two studies more comprehensively based on deeper theoretical grounds would likely be better suited for an independent manuscript.

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Author response:

We read the Assessment as identifying two decisive gaps: (i) claims of group differences are supported by within-group tests rather than by a test of the group X condition interaction, and (ii) the drift-diffusion modeling is not yet validated or fit in a framework that permits group comparison. We agree with both, and we do not defend the current versions of these analyses. The revision will rebuild them rather than supplement them. We also agree with the reviewers that several of our conclusions about “internal beliefs” are currently stated more strongly than the analyses support, and these will be scaled back to what the modeling can carry.

Below we first note factual errors and internal inconsistencies in the manuscript that the editors asked us to flag promptly, then summarize the planned revisions, then respond to each public review comment in turn.

(1) Corrections and clarifications for the record

Reviewer #2 identified one outright error in our text, and in re-checking the manuscript we found several further inconsistencies. We list them here so that they are on the record alongside the first version of the Reviewed Preprint. In each case the reviewers' reading of the manuscript is correct and the manuscript is at fault.

(a) Aggressive investors and pupil modulation (Reviewer #2, 4.3). Our Results text states that “aggressive investors showed no significant pupil modulation by ambiguity,”. This is incorrect and contradicts our own Fig. 2d, which reports a significant, ambiguous vs. non-ambiguous difference in all three groups, including aggressive investors ($T(31) = 2.74$, $P = 0.0304$, Bonferroni-corrected). The figure and its statistics are correct; the text is wrong. The interpretive claim built on it - that aggressive investors show “blunted” arousal - is therefore unsupported and will be removed. The revised manuscript will state the correct within-group result and will test group differences directly rather than by contrasting significant against non-significant within-group tests.

(b) Within-group versus between-group claims. Relatedly, our Results state that ambiguity-related pupil differences under the subjective model are “no longer significant relative to zero,” whereas the Discussion describes them as no longer differing across groups. These are different claims, and only the first was tested. This conflation runs through several of our physiological conclusions and is the same problem the Assessment identifies. It will be resolved by replacing these statements with explicit between-group and interaction tests.

(c) Sample description (Reviewer #1, 5). The numbers are not contradictory but are certainly underspecified, and we accept that as written they cannot be reconciled by a reader. To state them plainly: 57 unique individuals each completed one to three sessions, yielding 108 sessions; 7 sessions were incomplete and 5 showed no response variability, leaving 96 sessions with usable behavior; of these, 95 had usable pupil data and 79 usable EEG. The three strategy groups are tertiles of these 96 sessions (32 each), and the smaller Ns in Figs. 2-4 (N = 31, 29, 25) reflect modality-specific exclusions within each tertile. The revision will include a participant/session flow diagram and a table reporting how many individuals contributed one, two, or three sessions, together with per-figure Ns.

(d) DDM fitting procedure (Reviewer #1, 11). One clarification: the DDMs were fit separately for each participant, not separately per group (Methods, Section 4.6); group comparisons were then performed on the participant-level parameter estimates. We note this only for accuracy of the record. The reviewer's substantive objection is unaffected and we accept it: comparing parameters estimated in independent per-participant fits does not constitute a test of group differences within a common statistical framework, and it cannot test interactions.

(e) Inconsistent specification of the EEG regressor. The trial-wise EEG covariate is described in one paragraph of Methods 4.6 as 8-13 Hz power averaged over 0-0.5 s, and in the text following Eq. 3 as a 1315 Hz difference over 0.1-0.4 s. The former corresponds to the analysis actually performed. We will correct Eq. 3's description and report the frequency band and window once, unambiguously.

(f) Time-locking and figure/caption errors. As Reviewer #1 notes (comment 14), Methods describe stimulus-locked epochs (-0.25 to 1 s) while Figs. 2-3 are labeled relative to decision onset over -1 to 2 s. We will state for each analysis whether it is stimulus- or response-locked and harmonize axis labels accordingly. In addition: the Fig. 3 caption reads "N = 25 for ideal and aggressive; N = 29 for aggressive," where the second instance should read conservative; and Section 2.6 cites Fig. 1b and 1c for the leadership and team-performance results, which are Fig. 4e and 4f.

(g) Delta/theta claims in the Discussion. Our Discussion attributes early delta- and theta-band enhancements to ideal investors. No such effects appear in our own time-frequency results, which report frontal beta-range and parietal alpha/low-beta clusters. These Discussion statements are not supported by the data presented and will be deleted. This also bears on Reviewer #1's comment 13, since it removes the only interpretation that depended on the low-frequency edge of our filter passband.

(2) Summary of planned revisions

(2.1) A single statistical framework with explicit interaction tests. All group comparisons will be replaced by unified models that include group, condition, and their interaction, with sessions nested within participants. Choice will be modeled with a generalized linear mixed model of the form invest ~ ambiguity × group + trial + (1 + ambiguity | participant/session); decision time with the corresponding linear mixed model including random slopes for ambiguity (Reviewer #1, 15). Time-resolved pupil and time-frequency EEG effects will be evaluated using cluster-based permutation tests on the group-by-condition interaction statistic rather than by aggregating within-group tests. Where our claim is that an effect is

absent, most importantly, that ambiguity-related pupil differences vanish under subjective valuation, we will support it with equivalence testing and Bayes factors rather than with a non-significant P value, since a null result is not evidence for the null.

(2.2) Continuous analyses as primary; grouping justified or abandoned. We accept that trichotomizing a continuous decision tendency requires justification that we did not provide. The revision will (i) define a continuous EV-consistency index and re-run every key analysis with it as a continuous predictor, establishing that the principal conclusions do not depend on the split. The “ideal” label implies a normative optimality we have not demonstrated and will be replaced with descriptive labels (EV-consistent, EV-exceeding, EV-shortfall).

(2.3) Full specification, validation, and reliability of the belief parameter k. We agree the current description of k is inadequate. The revision will give the generative choice model in full, and explicitly state the estimation procedure and parameter bounds.

(2.4) Rebuilt and validated drift-diffusion modeling. The boundary will be freed and estimated per participant/session, so that variance is no longer forced into the drift term. We will report whether the group effect on baseline drift survives.

(2.5) Report why repeated sessions are treated as independent samples. We will conduct additional behavioral analyses to show repeated sessions from the same individual are sufficiently independent to be analyzed as unique samples. In particular, we will examine whether within-participant similarity across sessions is greater than cross-participant similarity. These analyses will provide direct evidence for whether sessions can reasonably be treated as separate samples rather than requiring sessions to be nested within participants.

(2.6) Sharper framing and appropriately scaled claims. We will remove the framing that positions the field as treating ambiguity aversion as uniform and instead situate the work within literature that already documents heterogeneity in ambiguity attitudes. The distinction between ambiguity aversion and the internal representation of ambiguity will be made explicit, with the latter identified as our actual question. Claims about “internal belief models” will be restated in terms of what is estimated. Physiological hypotheses will be stated as specific, directional, falsifiable predictions rather than by appeal to the broad range of processes EEG has been linked to.

(2.7) Quality control for pupillometry, EEG, and the VR context. We will report blink rates and counts, proportion of interpolated samples, trials and channels rejected, and ICA components removed. We will also report validate the luminance GLM.

(2.8) The collaborative task. The Apollo Distributed Control Task preceded the Lottery Choice Task by design, so it must be reported as part of the protocol regardless of the leadership analysis. However, we agree that the leadership and team-performance analyses are not sufficiently motivated to carry the interpretive weight currently given them. They will be moved to a clearly labeled exploratory section, removed from the Abstract and framing, and presented without causal or trait-level interpretation.

(3) Timeline and next steps

The revisions above require refitting the behavioral, physiological, and computational analyses rather than adding to them, including hierarchical model fitting, parameter recovery, and new quality-control analyses. We therefore anticipate submitting the revised manuscript within approximately three months, and would welcome guidance if the editors would prefer a different schedule. We are content for the first version of the Reviewed Preprint to be published with this provisional response attached.

We are grateful to both reviewers for the time invested in this manuscript. Several of the problems they identify are ones we should have caught ourselves, and the paper will be considerably stronger for their having been raised now rather than after publication.

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