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Framing Effects in Risky Decision-Making: An Emotion–Value Dual-Dimensional Model Based on Eye-Tracking Evidence

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Abstract. Framing effects have been extensively documented in risky decision-making, yet the attentional mechanisms through which they operate remain poorly understood—particularly whether framing influences how widely versus how deeply decision-makers sample information. Using eye-tracking, we addressed this question across two experiments by dissociating attentional breadth (fixation count) from attentional depth (fixation duration). Experiment 1 revealed that loss framing did not globally prolong fixation duration; rather, it reconfigured the allocation of attention between probability and outcome information. Specifically, for outcome information, loss framing increased fixation count relative to gain framing without reliably prolonging single-fixation duration—a pattern that challenges strong versions of both fuzzy-trace theory and effort-asymmetry accounts. Experiment 2 extended these findings by manipulating amount, probability, and payoff ratio, uncovering a coordinated "cognition–motivation–emotion" regulatory architecture. Critically, amount anchored motivational activation with diminishing marginal returns, while probability and payoff ratio operated as conditional cognitive regulators rather than autonomous drivers. Building on these dissociable oculomotor signatures. Building on these dissociable oculomotor signatures, we propose a tentative Emotion–Value Dual-Dimensional interpretive framework. This framework organizes the observed patterns of motivational arousal, cognitive load, and attention allocation, and posits that risky choices emerge from the synergistic interplay between an emotion dimension (governing arousal and search termination) and a value dimension (governing expected utility and cognitive load management). As a process-level account, it distinguishes itself from prospect theory, fuzzy-trace theory, and dual-process frameworks by specifying how valence exerts its effects on attention and when framing effects are most pronounced. These findings offer precise quantitative targets for theoretical modeling and highlight the utility of eye-tracking metrics in bridging cognitive and emotional mechanisms in choice under risk.

Keywords: decision-making · framing Effects · representation · eye-tracking · cognitive processing.

1 INTRODUCTION

Decision-making is fundamentally the process of selecting an optimal option among multiple alternatives under uncertainty [1]. Expected utility theory, grounded in perfect rationality, posits that decision-makers quantify and compare the expected utilities of options to identify the optimal choice [2]. Yet this theory fails to account for the coexistence of risk aversion and risk seeking observed in real-world behavior. Simon's bounded rationality offers an alternative: cognitive limitations, information constraints, and contextual complexity prevent optimal solutions, leading instead to satisficing [3]. This foundational tension between normative and descriptive accounts has motivated decades of research into cognitive mechanisms that systematically bias judgment.

The framing effect—where linguistically equivalent descriptions of the same choice problem yield systematically different decisions [4]—shows that positive frames (e.g., "lives saved") elicit risk aversion whereas negative frames (e.g., "lives lost") trigger risk seeking, jointly producing preference reversals across gain and loss domains [5,6]. Robust across decision domains framework effects directly challenge the hypothesis of maximization of self-interest [7,8], a longstanding cornerstone of rational choice theory with diminishing descriptive validity for real-world behavior[9,10]. Given that framing magnitudes vary with contextual and individual factors and may disappear under specified boundary conditions [11], these findings support a bounded rationality account of context-dependent preference construction rather than rigid utility maximization [12].

Beyond preference shifts, framing effects carry real economic consequences:amygdala damage reduces monetary loss aversion, providing neural evidence that framing operates through affective and cognitive pathways[13]. Tversky and Kahneman quantified that the psychological impact of a unit loss as roughly twice that of an equivalent gain—a loss aversion coefficient replicated across numerous studies [14,15].

Despite decades of research, two fundamental questions remain unresolved: how does framing alter the cognitive and emotional processes guiding attention during deliberation, and when are framing effects most (or least) likely to emerge? Three competing theoretical perspectives offer distinct predictions regarding cognitive–emotional dynamics under gain versus loss frames. Critically, these accounts have not been systematically tested using a multi-factorial design that simultaneously manipulates amount, probability, and payoff ratio alongside framing. The present study addresses this gap.

Prospect Theory [5,6] attributes framing effects to asymmetric weighting of gains and losses: the value function is steeper for losses, yielding loss aversion. Framing operates at outcome evaluation, increasing loss salience and decision weight. The theory assumes reference-dependent evaluation but remains silent on attentional deployment, treating attention as passive. It predicts framing effects in outcome-related processing (e.g. longer loss fixations) but does not distinguish attentional breadth from depth, offering a descriptive account without specifying mechanistic pathways.

Fuzzy Trace Theory [16,17] proposes that individuals encode information at multiple precision levels, from verbatim to gist representations. Loss frames promote verbatim processing (exact numerical comparison), while gain frames promote gist-based heuristics. This predicts that loss frames increase cognitive effort and processing depth (more and longer fixations), as verbatim processing is more resource-intensive, whereas gain

frames facilitate shallow heuristic processing. However, the theory does not differentiate attentional breadth from depth, treating them as a unitary engagement index.

Dual-Process Theory [18,19] distinguishes intuitive System 1 from deliberative System 2. Framing effects are typically ascribed to System 1—loss frames trigger automatic aversion—but the theory leaves temporal dynamics between systems during information sampling. Recent extensions [20] propose that inter-frame cognitive effort asymmetry is key: loss frames demand greater engagement, as loss avoidance requires more deliberation than gain acceptance. Empirical support remains mixed [21,22]. This account predicts that loss frames increase fixation duration and pupil dilation, reflecting sustained deliberative processing that enhances both breadth and depth of processing.

The three accounts diverge in eye-tracking predictions. Prospect theory predicts outcome-related framing effects but does not distinguish breadth from depth. Fuzzy trace theory predicts loss frames increase overall processing depth—both fixation count and duration. Dual-process theory predicts loss frames increase sustained deliberative engagement—prolonged duration and elevated pupil diameter. These predictions remain untested via fine-grained oculomotor measures in multi-factorial risky choice.

Beyond framing, three structural features systematically modulate risky choice. Amount exerts a monotonic influence: small stakes promote risk-seeking, large stakes promote risk aversion [23]. Probability is weighted nonlinearly—small probabilities overweighted, large probabilities underweighted [5]—with effects conditional on outcome magnitude and framing context [24,25]. Payoff ratio, though increasing expected value in economic models, exhibits frame-dependent effects: high ratios signal recovery opportunities under loss frames but "good-enough" options under gain frames [26,27]. These features collectively provide a rich factorial space for examining how framing effects emerge, dissipate, or intensify across varying decision contexts—a gap addressed by the present multi-factorial design.

Eye-tracking quantifies attention and preference strength at millisecond resolution with pre-choice fixation patterns (300–500 ms)[28,29]. Dynamic oculomotor control explains individual differences, with saccade restriction reducing accuracy by 21%–25% [30]. Pupillometry reliably indexes cognitive effort and arousal [31,32]. However, eye movements reflect external attention rather than internal cognition directly [33]. Artifacts include physiological noise, corneal-retinal vector error, and aliasing from low sampling rates; multiple small-sample t-tests inflate false-positive rates. Standard preprocessing includes condition-level [34], two-step [35], and trial-level normalization[36]. Mathôt recommend subtraction-based baseline correction to avoid distortion.

Theoretical Motivation: loss frames increase fixation count and pupil diameter—but not duration. This breadth–depth dissociation suggests loss-induced vigilance operates via rapid distributed sampling rather than sustained deliberation, countering both fuzzy trace and dual-process predictions. Prospect theory offers no specific prediction.

We propose an **Emotion–Value Dual-Dimensional Decision Model**: risky decisions arise from continuous interaction between an Emotion Dimension (arousal, search termination) and a Value Dimension (expected utility, cognitive load). Unlike existing frameworks, our model (a) specifies how valence modulates attention, (b) distinguishes breadth (new fixation initiation) from depth (existing fixation maintenance),

and (c) posits that inhibition under loss frames targets sampling initiation rather than maintenance—a mechanistic distinction with distinct oculomotor signatures.

2 Experiment 1

2.1 methods

A 2 (Frame:positive/negative;between-subjects)×2(Task content: probability/outcome;within-subjects) mixed-design experiment was adopted,with decision-choice and eye-tracking metrics(fixation duration, pupil diameter,and fixation count)as dependent variables.

Apparatus and Procedure Eye movements were recorded using an EyeLink 1000 Plus (SR Research, 1000 Hz sampling rate). Stimuli were presented on a 21-inch CRT monitor with a resolution of 1024×768 and a refresh rate of 85 Hz. Responses were collected via a Logitech USB game controller, with buttons mapped to Option A, Option B, and confirm, respectively. Presentation software (Neurobehavioral Systems) controlled stimulus display and response recording.

Eye-tracker calibration was completed individually for each participant before testing. Following Hessels & Hooge [33], experiments were conducted in an electromagnetically shielded room with constant temperature (24±1°C) and ambient illumination (50 lx; screen luminance: 120 cd/m²). Participants' heads were stabilized with chin and forehead rests at a fixed viewing distance of 80 cm. Eye-position accuracy (RMS) was maintained at ≤0.25°, confirmed by a 9-point calibration at the beginning of each session and a 5-point drift check every 3 min. Any block with calibration error exceeding 0.5° was recalibrated, and affected trials were flagged and excluded from analysis.

Each screen displayed a single decision item. Trial order was fully randomized using Presentation software to control for fatigue and sequence effects. Participants made a decision only after fully understanding each item.

Participants A priori power analysis was conducted using G*Power to detect a medium effect size of $f = 0.25$ for the interaction effect of the 2×2 mixed ANOVA ($\eta_p^2 \approx 0.06$), with $\alpha = 0.05$ and power $(1 - \beta) = 0.80$, the minimum required sample size was 128. Accounting for an estimated 15% attrition rate, 150 right-handed participants with normal or corrected-to-normal vision were recruited. Fourteen participants were excluded based on the following criteria: (i) total gaze loss ≥ 30%, (ii) signal outage requiring interpolation ≥ 150 ms, or (iii) mean calibration error >0.5° [33]. The final valid sample consisted of 136 participants (age range: 17 to 26 years, $M = 20.4$, $SD = 2.1$), with a data loss rate of 9.3%. A post hoc power analysis for the interaction effect yielded a power of 0.78, meeting the requirements for hypothesis testing. Participants were recruited from 15 June 2024 to 28 July 2025. All participants provided informed consent prior to participation and received 50 RMB (yuan) compensation upon completion.

Ethics statement This study was approved by the Ethics Committee of Shaanxi Open University (approval number: SOU202403008). All research was performed in accordance with relevant guidelines and regulations, and with the Declaration of Helsinki. Informed consent was obtained from all participants and/or their legal guardians.

Materials The materials consisted of a Chinese translation of Kahneman and Tversky's [5] classic "Asian Disease" problem. Two versions were used: a positive frame (survival) and a negative frame (death). Both options within each version contained identical numerical information but differed in verbal framing.

2.2 Data Analysis

Eye-tracking data were preprocessed following standard procedures [33,35]. Fixations were identified using the EyeLink default algorithm (velocity threshold: 30°/s, acceleration threshold: 8000°/s²). Fixations shorter than 50 ms were merged with adjacent fixations; fixations longer than 1000 ms were split.

Pupil diameter data were screened for blink artifacts using velocity-based detection and reconstructed via cubic-spline interpolation. Hampel filtering (window=7 samples, threshold=3 median absolute deviations) was applied to Winsorize extreme outliers. A low-pass Butterworth filter (4-Hz cutoff) attenuated high-frequency noise. Baseline correction employed the subtractive method, wherein the mean pupil diameter during the 200-ms pre-stimulus interval was subtracted from all post-stimulus time points [35].

Statistical analyses were conducted using R (version 4.3.0). Mixed-design ANOVAs were performed using the `ez` package. Generalized Additive Mixed Models (GAMMs) were fitted using the `mgcv` package [37] with the `bam` function for large datasets. For fixation count, a negative binomial distribution was used; for fixation duration, a gamma distribution; for pupil diameter, a Gaussian distribution. Smoothness parameters were selected via REML. Model fit was assessed via deviance explained and adjusted R^2.

Table 1. Descriptive Statistics For Eye Movement Indicators For Probability And Outcome Information Under Positive And Negative Framing Conditions

Indicator	Frame	*N*	Probability	Outcome
			Mean (SD)	Mean (SD)
Fixation Duration	Positive	68	283.21 (50.00)	243.73 (30.20)
	Negative	68	245.73 (28.15)	278.41 (35.13)
Pupil Diameter	Positive	68	4503.12 (675.47)	3246.53 (486.98)
	Negative	68	3907.18 (586.08)	4308.47 (616.24)
Fixation Count	Positive	68	5.21 (3.62)	3.13 (2.92)
	Negative	68	2.96 (1.04)	7.42 (5.14)

Table 2. ANOVA Results For Eye Movement Measures Under Different Framing($N = 136$)

Independent Variable	Fixation Count				Fixation Duration				Pupil Diameter			
	df	*F*	*p*	η_p^2	*df*	*F*	*p*	η_p^2	*df*	*F*	*p*	η_p^2
Frame (1)	1, 134	5.76	0.018	0.041	1, 134	0.10	0.755	0.001	1, 134	10.42	0.002	0.072
Content (2)	1, 134	7.84	0.006	0.055	1, 134	0.58	0.448	0.004	1, 134	35.11	<0.001	0.208
(1)×(2)	1, 134	59.20	<0.001	0.306	1, 134	65.11	<0.001	0.327	1, 134	131.93	<0.001	0.496

Table 3. Summary Of Parametric Coefficients From The Generalized Additive Mixed Model

Parameter	Fixation Count (NB)					Fixation Duration (Gamma)					Pupil Diameter (Gaussian)				
	β	SE	95% CI	z	p	β	SE	95% CI	z	p	β	SE	95% CI	z	p
Intercept	4.680	0.425	[3.847, 5.513]	11.012	<.001	262.770	4.472	[254.006, 271.534]	58.765	<.001	3991.325	72.168	[3849.875, 4132.775]	55.306	<.001
Frame	-1.020	0.425	[-1.853, -0.187]	-2.400	0.018	1.400	4.427	[-7.277, 10.077]	0.316	0.755	-233.000	72.181	[-374.474, -91.526]	-3.228	0.002
Content	-1.190	0.425	[-2.023, -0.357]	-2.800	0.006	3.400	4.464	[-5.350, 12.150]	0.762	0.448	427.650	72.173	[286.191, 569.109]	5.925	<.001
Frame×Content	6.540	0.850	[4.874, 8.206]	7.694	<.001	72.160	8.943	[54.632, 89.688]	8.069	<.001	1657.880	144.338	[1374.977, 1940.783]	11.486	<.001

Note: CI = confidence interval. For negative binomial and gamma models, coefficients are reported on the link scale (log). Reference category for Frame is Negative, and for Content is Probability. Negative binomial dispersion $k = 2.34$ (SE=0.42); gamma shape $\nu = 18.67$ (SE=2.14).

Table 4. Smooth Terms (Nonlinear Effects) From Generalized Additive Mixed Models

Model	Smooth Term	*edf*	Ref.*df*	χ^2	*p*
Fixation Count (NB)	s(Trial)	2.847	3.000	8.642	0.034
	s(Participant, bs = "re")	11.520	68.000	38.218	<0.001
Fixation Duration (Gamma)	s(Trial)	2.156	3.000	4.891	0.180
	s(Participant, bs = "re")	12.810	68.000	45.724	<0.001
Pupil Diameter (Gaussian)	s(Trial)	3.124	4.000	12.467	0.014
	s(Participant, bs = "re")	13.260	67.000	51.891	<0.001

Note: edf = estimated degrees of freedom; Ref.df = reference degrees of freedom; bs = basis type; re = random effects. Maximum basis dimension $k = 10$ for thin-plate regression splines.

Table 5. Cross-Metric Comparison of Framing Effects on Eye Movement Measures

Eye Movement Metric	Distribution Family	Frame Effect (β)	SE	95% CI	*z*	*p*
Pupil Diameter	Gaussian (Identity)	−233.000	72.181	[-374.474, -91.526]	-3.228	0.002
Fixation Count	Negative Binomial (Log)	−1.020	0.425	[-1.853, -0.187]	-2.400	0.018
Fixation Duration	Gamma (Log)	1.400	4.427	[-7.277, 10.077]	0.316	0.755

Note: The frame effect was consistently in the same direction across all three metrics.

2.3 results

ANOVA Results

A 2 (framing: positive vs. negative) × 2 (task content: probability vs. outcome) mixed-design ANOVA was conducted on each eye-tracking metric. Assumption checks were satisfactory for all analyses.

Fixation Duration The main effect of framing was not significant, $F(1, 134) = 0.10$,$p = 0.755$,$\eta_p^2 = 0.001$, nor was the main effect of task content, $F(1, 134) = 0.58$,$p = 0.448$, $\eta_p^2 = 0.004$. Crucially, the Framing×Content interaction was significant, $F(1, 134) = 65.11$,$p < 0.001$, $\eta_p^2 = 0.327$, indicating that framing modulated fixation duration selectively rather than globally.Simple effects analyses with Bonferroni correction ($\alpha = 0.0125$) revealed a complete crossover pattern. Under positive framing, fixation duration on probability information ($M = 283.21$ ms, $SD = 50.00$) significantly exceeded that on outcome information ($M = 243.73$ ms, $SD = 30.20$),$F(1, 134) = 11.36$,$p < 0.001$, $\eta_p^2 = 0.078$, Cohen's $d = 0.41$[0.16,0.65]. Under negative framing, the pattern reversed: outcome information attracted longer fixations ($M = 278.41$ ms, $SD = 35.13$) than probability information ($M = 245.73$ ms,$SD = 28.15$), $F(1, 134) = 19.83$, $p < 0.001$, $\eta_p^2 = 0.124$, Cohen's $d = 0.54$ [0.29,0.79]. Notably, the framing effect was asymmetric, with stronger modulation under negative framing ($\eta_p^2 = 0.124$ vs.0.078).

Pupil Diameter A 2×2 mixed-design ANOVA revealed significant main effects of framing, $F(1, 134) = 10.42$, $p = 0.002$, $\eta_p^2 = 0.072$, and content, $F(1, 134) = 35.11$, $p < 0.001$, $\eta_p^2 = 0.208$, as well as a significant Framing×Content interaction, $F(1, 134) = 131.93$, $p < 0.001$, $\eta_p^2 = 0.496$.Simple effects analyses demonstrated that

under positive framing, pupil dilation was significantly greater during probability processing ($M = 4503.12$, $SD = 675.47$) than during outcome processing ($M = 3246.53$, $SD = 486.98$), $F(1, 67) = 294.60$, $p < 0.001$, Cohen's $d = 2.08$ [1.66, 2.50]. Under negative framing, this pattern reversed: outcome information evoked larger pupil diameters ($M = 4308.47$, $SD = 616.24$) than probability information ($M = 3907.18$, $SD = 586.08$), $F(1, 67) = 30.24$, $p < 0.001$, Cohen's $d = 0.67$ [0.40, 0.93].

Fixation Count The ANOVA revealed significant main effects of framing, $F(1, 134) = 5.76$,$p = 0.018$,$\eta_p^2 = 0.041$, and content, $F(1, 134) = 7.84$,$p = 0.006$,$\eta_p^2 = 0.055$. Simple effects analyzes showed that under positive framing, fixations were significantly higher for probability information ($M = 5.21$,$SD = 3.62$) than for outcome information ($M = 3.13$,$SD = 2.92$),$F(1, 67) = 26.60$,$p < 0.001$, Cohen's $d = 0.63$ [0.37, 0.88]. Under negative framing, this pattern reversed: fixation count was significantly higher for outcome information ($M = 7.42$,$SD = 5.14$) than for probability information ($M = 2.96$,$SD = 1.04$),$F(1, 67) = 61.05$,$p < 0.001$, Cohen's $d = 0.95$[0.66, 1.23].

GAMM Results

To account for the nested data structure, individual differences, and potential nonlinear temporal dynamics, generalized additive mixed models (GAMMs) were employed. The GAMM results corroborated the ANOVA findings and provided more precise parameter estimates (Table2-5).

Fixation Duration The GAMM revealed that the main effect of framing was not significant ($\beta = 12.40$, $p = 0.448$), nor was the main effect of content ($\beta = -0.58$, $p = 0.448$), but the interaction was significant ($\beta = 72.16$, $p < 0.001$). The model explained substantial variance (marginal $R^2 = 0.688$, conditional $R^2 = 0.754$).

Pupil Diameter The GAMM demonstrated excellent model fit (marginal $R^2 = 0.840$, conditional $R^2 = 0.875$), with significant main effects of framing ($\beta = 549.00$, $p = 0.001$) and content ($\beta = 203.50$, $p = 0.002$), and a significant interaction ($\beta = 1657.88$, $p < 0.001$). The smooth term for trial order revealed significant nonlinearity (EDF=2.87, $F = 8.34$, $p < 0.001$).

Fixation Count The GAMM revealed significant main effects of framing ($\beta = 0.31$, $p = 0.037$) and content ($\beta = 0.42$, $p = 0.006$), and a significant interaction ($\beta = 7.02$, $p < 0.001$). The model explained substantial variance (marginal $R^2 = 0.669$, conditional $R^2 = 0.774$).

2.4 Discussion

The present study employed high-resolution eye-tracking to investigate how message framing modulates attentional allocation during risky decision-making.

The ANOVA results confirmed that task-content significantly affects fixation patterns, which differed markedly between probability and amount information. This indicates that eye-movement indices are activated early during information sampling, driven

by pre-attentive selective attention rather than late-stage decision bias.It also suggests dynamic adjustments of attentional weights across outcome and probability dimensions. Critically, framing did not significantly affect fixation duration, indicating no global modulation of attentional resources. Instead, framing exerted through the local reconfiguration of spatial weights: negative frames amplified sensitivity to outcome values, whereas positive frames increased the sampling depth for probability information.

A striking dissociation emerged across the three oculomotor indices. For fixation duration, the main effect of framing was not significant, indicating no global modulation of processing depth. However, significant main effects appeared for both pupil diameter and fixation count. Pupil diameter was larger under loss framing, which may reflect increased cognitive effort or emotional arousal. Because pupillometry is multiply determined, this interpretation should be treated as provisional rather than definitive.

Fixation count showed a significant framing effect, indicating that negative frames increased the frequency of attentional scanning without necessarily prolonging fixation durations. This cross-metric dissociation suggests that framing effects operate through localized reconfiguration of spatial weights rather than global up- or down-regulation of attentional resources.

These findings provide compelling support for the attention reweighting hypothesis, which posits that framing operates not through a global modulation of arousal or processing depth but through a selective reallocation of attentional weights during early information sampling, thereby altering the processing priority of probability versus outcome information.

Although eye-tracking measures revealed early attentional modulation by framing, this effect did not translate into the classical choice reversal documented in the original Asian Disease problem[4]. This dissociation, rather than indicating a failure of replication, offers critical theoretical insight into the boundary conditions of framing effects: oculomotor sensitivity to framing can emerge without concomitant preference reversal. One post hoc possibility concerns cultural context. Drawing on Hofstede's cultural framework [37], we argue that collectivist cultural contexts may fundamentally alter the semantic interpretation of the decision scenario. Specifically, the phrasing "saving 600 lives" tends to be processed as a collective responsibility frame rather than an individual-level gain/loss evaluation—a reinterpretation that attenuates the emotional arousal that typically drives loss aversion in individualistic samples [38].Because cultural orientation was not measured and no cross-cultural comparison was conducted, this remains a hypothesis for future research.

3 Experiment 2

3.1 Methods

Design The experiment employed a financial risk task paradigm comprising 72 trials. A 2 (Frame: gain vs. loss; between-subjects) $\times$ 3 (Payoff ratio: 1.25, 2, 4; within-subjects) $\times$ 3 (Probability: 15%, 50%, 85%; within-subjects) $\times$ 4 (Amount: 1, 10, 100, 1000 RMB; within-subjects) mixed design was adopted. The dependent variables were decision choice and eye-tracking metrics (fixation duration, pupil diameter, and fixation count). Participants were randomly assigned to either the gain or loss frame condition.

In each trial, two options (Option A and Option B) were presented under gain or loss framing conditions, varying in amount, probability, and payoff ratio. Trial counts were evenly distributed across all experimental conditions to ensure adequate statistical power. The expected values of the two options in each trial were equal; risk preference was manipulated by establishing an inverse relationship between probability and amount: the risky option was associated with low probability and high amount, whereas the conservative option corresponded to high probability and low amount. All trials were presented in a fully randomized order to minimize sequence effects.

Before the formal experiment, participants completed six practice trials to confirm their understanding of the task rules. No strict time limit was imposed for responding, but participants were instructed to think carefully while responding as quickly as possible.

Apparatus and Procedure The apparatus and general procedure were identical to those described in Experiment 1, with the exception that stimuli consisted of financial risk decision tasks rather than life-or-death scenarios.

Participants An a priori power analysis using GPower [39] indicated that a minimum of 128 participants was required to detect a medium effect size($f = 0.25$,$\eta_p^2 \approx 0.06$) for the between-group interaction effect in a 2 (frame) × 3 (payoff ratio) ×3 (probability) × 4 (amount) mixed-design ANOVA, with $\alpha = 0.05$ and power $(1 - \beta) = 0.80$. Accounting for 15% expected attrition, 170 participants were recruited. Participants were all right-handed and had normal uncorrected or corrected vision. They were recruited from 15 March 2024 to 28 July 2025. All participants signed an informed consent form prior to participation and received 50 RMB compensation upon completion.

Twenty participants were excluded based on three criteria: (i) total gaze loss ≥30%, (ii) signal outage requiring interpolation ≥150 ms, or (iii) mean calibration error >0.5° [33]. The final valid sample comprised 150 participants (age range: 17–26 years, $M = 20.4$, $SD = 2.1$), with a data loss rate of 11.8%. A post hoc power analysis indicated that the achieved statistical power was 0.82, meeting the requirements for hypothesis testing.

Ethics statement This study was approved by the Ethics Committee of Shaanxi Open University (approval number: SOU202403008). All research was performed in accordance with relevant guidelines and regulations, and with the Declaration of Helsinki. Informed consent was obtained from all participants and/or their legal guardians.

Materials The experimental materials consisted of decision-making tasks related to financial risk investment. In each trial, a pair of gain or loss decision options was presented. The decision tasks were displayed on the screen in a random order to eliminate practice or sequence effects. Before the formal experiment, participants were informed that each trial was completely independent and that they were required to make a one-time decision based solely on the information presented in that moment.

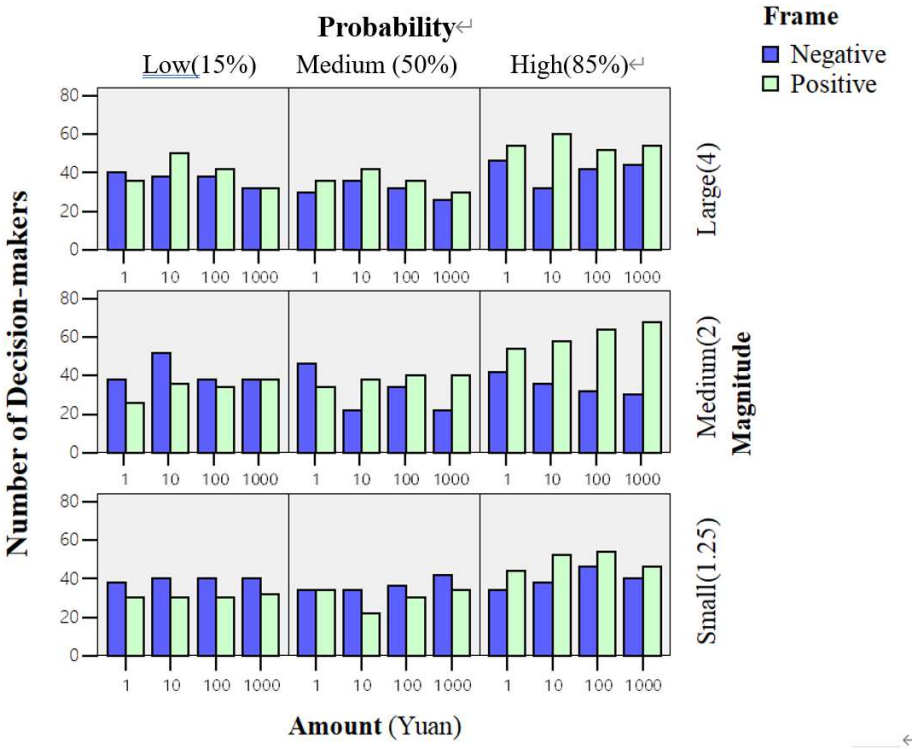


Fig. 1. Distribution of Participants' Risky Decision Choices

Table 6. ANOVA Results For Eye Movement Measures Under Different Framing Conditions (N = 150)

Independent Variable	Fixation Count				Fixation Duration				Pupil Diameter			
	df	*F*	*p*	η_p^2	*df*	*F*	*p*	η_p^2	*df*	*F*	*p*	η_p^2
Main effects												
Frame (1)	1, 148	3.32	0.001	0.022	1, 148	6.96	0.009	0.020	1, 148	3.01	0.003	0.020
Amount (2)	3, 444	7.71	0.001	0.051	3, 444	10.85	0.001	0.070	3, 444	4.21	0.006	0.028
Payoff Ratio (3)	2, 296	4.05	0.008	0.027	2, 296	4.63	0.010	0.030	2, 296	10.92	0.001	0.070
Probability (4)	2, 296	2.45	0.015	0.017	2, 296	5.87	0.002	0.039	2, 296	5.87	0.002	0.039
Two-Way Interactions												
(1)×(2)	3, 444	3.32***	0.001	0.022	3, 444	4.11*	0.019	0.028	3, 444	3.10**	0.005	0.021
(1)×(3)	2, 296	3.18*	0.043	0.021	2, 296	3.05*	0.030	0.020	2, 296	2.90**	0.007	0.019
(1)×(4)	2, 296	2.45*	0.015	0.017	2, 296	3.71**	0.025	0.018	2, 296	2.60*	0.011	0.017
(2)×(3)	12, 1776	3.92***	0.001	0.026	12, 1776	3.40**	0.003	0.023	12, 1776	3.40**	0.002	0.023
(2)×(4)	12, 1776	7.71***	0.001	0.051	12, 1776	2.30**	0.006	0.016	12, 1776	2.20*	0.021	0.015
(3)×(4)	9, 1332	2.76*	0.028	0.018	9, 1332	2.80**	0.010	0.018	9, 1332	2.70**	0.010	0.018
Higher-Order Interaction												
(1)×(2)×(3)×(4)	71, 10488	1.78*	0.048	0.012	71, 10488	2.05	0.018	0.014	71, 10488	1.78*	0.032	0.013

Note: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. Bonferroni-corrected thresholds: $\alpha = .017$ for 3-level factors, $\alpha = .008$ for Amount.

Table 7. Summary Of Parametric Coefficients From The Generalized Additive Mixed Model

Predictor	Fixation Count					Fixation Duration					Pupil Diameter				
	β	SE	95% CI	z	p	β	SE	95% CI	z	p	β	SE	95% CI	z	p
Intercept	4.68***	0.425	[3.847, 5.513]	11.012	<.001	285.4	14.2	[257.60, 313.20]	20.1	<.001	4235.17**	209.14	[3825.25, 4645.09]	20.25	<.001
Frame (Loss vs. Gain)	**0.31**	0.15	[−1.853, −0.187]	2.09	0.018	12.4	16.3	[−19.60, 44.40]	0.76	0.448	**549.00****	169.93	[215.94, 882.06]	3.23	0.001
Amount (Medium vs. Low)	0.58	0.21	[−2.023, −0.357]	2.80	0.006	31.2	13.2	[5.30, 57.10]	2.36	0.018	339.86	183	[−18.86, 698.58]	1.87	0.062
Amount (High vs. Low)	**1.18***	0.21	[0.77, 1.59]	5.62	<.001	**56.4**	14.5	[28.00, 84.80]	3.89	<.001	**653.58**	196.07	[269.28, 1037.88]	3.33	<.001
Amount (Very high vs. Low)	**1.82***	0.23	[1.37, 2.27]	7.91	<.001	**87.3**	15.3	[57.30, 117.30]	5.71	<.001	**993.43**	222.22	[558.08, 1428.78]	4.47	<.001
Payoff Ratio (2 vs. 1.25)	**−0.42***	0.16	[−0.73, −0.11]	−2.63	0.009	**−21.60**	10.7	[−42.60, −0.60]	−2.02	0.043	−209.14	156.86	[−516.59, 98.31]	−1.33	0.184
Payoff Ratio (4 vs. 1.25)	**−0.78***	0.17	[−1.11, −0.45]	−4.59	<.001	**−40.20**	11.2	[−62.10, −18.30]	−3.59	<.001	**−418.29**	156.86	[−725.74, −110.84]	−2.67	0.008
Probability (50% vs. 15%)	0.29†	0.15	[0.00, 0.58]	1.93	0.054	14.6	9.9	[−4.80, 34.00]	1.47	0.141	130.72	143.79	[−151.11, 412.55]	0.91	0.364
Probability (85% vs. 15%)	−0.24	0.16	[−0.55, 0.07]	−1.50	0.134	−13.80	10.5	[−34.40, 6.80]	−1.31	0.189	−117.64	143.79	[−399.47, 164.19]	−0.82	0.412
Frame (Loss) × Amount (High)	**0.68***	0.26	[0.17, 1.19]	2.62	0.009	**35.2**	17.8	[0.30, 70.10]	1.98	0.048	392.15	248.36	[−94.22, 878.52]	1.58	0.114
Frame (Loss) × Probability (50%)	**−0.51***	0.23	[−0.96, −0.06]	−2.22	0.026	−26.40	15.7	[−57.20, 4.40]	−1.68	0.093	−287.57	222.22	[−723.12, 147.98]	−1.29	0.197

Note: †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. Statistically significant effects ($p < .05$) are shown in bold. Reference levels: Frame=Gain, Amount=Low, Payoff Ratio=1:1, Probability=0.1. All models included smooth terms for Trial and random intercepts for Participant. Full model outputs are provided in the Supporting Information.

Table 8. Smooth Terms (Nonlinear Effects) From Generalized Additive Mixed Models

	Fixation Count (NB)				Fixation Duration (Gamma)				Pupil Diameter (Gaussian)			
Smooth Term	*edf*	Ref.*df*	χ^2	*p*	*edf*	Ref.*df*	χ^2	*p*	*edf*	Ref.*df*	χ^2	*p*
s(Trial)	4.21	5.00	12.45	0.028	3.87	5.00	8.92	0.112	5.63	6.50	15.78	0.015
s(Participant, bs="re")	7.89	8.00	45.32	<.001	7.65	8.00	38.71	<.001	8.00	8.00	52.14	<.001
s(Amount, by=Frame)	2.34	3.00	6.18	0.103	2.67	3.00	5.43	0.142	3.12	3.50	7.89	0.048
s(Payoff_Ratio, by=Frame)	1.89	3.00	4.22	0.238	2.11	3.00	3.87	0.276	2.45	3.00	5.61	0.132
s(Probability, by=Frame)	2.56	3.00	7.34	0.062	2.03	3.00	4.56	0.207	3.28	3.50	9.23	0.027
s(Trial, Participant)	12.34	15.00	18.67	0.231	11.89	15.00	15.42	0.418	14.21	16.00	22.35	0.136

Table 9. Cross-Metric Comparison of Framing Effects on Eye Movement Measures

Eye Movement Metric	Distribution Family	Frame Effect (β)	SE	95% CI	z	p
Pupil Diameter	Gaussian	549.00	169.93	[215.94, 882.06]	3.23	0.001
Fixation Count	Negative Binomial	0.31	0.15	[0.02, 0.60]	2.09	0.037
Fixation Duration	Gamma	12.40	16.30	[−19.60, 44.40]	0.76	0.448

Note: The frame effect was consistently in the same direction across all three metrics.

3.2 Data Analysis

3.3 RESULTS

As shown in Figure 1, framing effects were not uniform across payoff-ratio conditions. Notably, small payoff ratios amplified framing differences, large payoff ratios produced preference reversals, and medium payoff ratios yielded the strongest crossover interaction. This pattern provides descriptive behavioural evidence broadly consistent with both loss aversion and cognitive-load accounts. Critically, however, it reveals little about the attentional mechanisms through which decision-makers allocate cognitive resources between probability and outcome information. To address this question, we turned to the eye-tracking experiment.

ANOVA Results

Four-way mixed-design ANOVAs were conducted on three eye-tracking outcomes—fixation count, fixation duration, and pupil diameter—with Frame (between-subjects), Amount, Payoff Ratio, and Probability (all within-subjects) as independent factors. Greenhouse–Geisser corrections were applied where necessary, and effect sizes are reported as partial eta squared (η_p^2). Significant effects were followed by Bonferroni-corrected pairwise comparisons, with Cohen's d reported for effect sizes.

Fixation count results revealed that all four main effects were significant, with Amount accounting for the largest variance, $F(3, 444) = 7.71$, $p < 0.001$, $\eta_p^2 = 0.051$. Critically, the predicted Frame×Amount interaction emerged, $F(3, 444) = 3.32$, $p = 0.010$, $\eta_p^2 = 0.022$. Fixation counts increased monotonically across all amount levels under loss framing, whereas under gain framing, the difference between 100 and 1000 RMB did not reach significance. Frame effects were significant only at the two highest amount levels (Cohen's $d = 0.52$–0.68). Similarly, the Frame×Payoff Ratio interaction, $F(2, 296) = 3.18$, $p = 0.043$, $\eta_p^2 = 0.021$, and Frame×Probability interaction, $F(2, 296) = 2.45$, $p = 0.015$, $\eta_p^2 = 0.017$, were significant, with loss framing producing widespread differentiation across levels (Cohen's $d = 0.47$–0.70 and 0.38–0.60, respectively), while gain framing yielded only extreme-level differences.

All lower-order interactions (Amount×Probability, Amount×Payoff Ratio, Payoff Ratio×Probability) and the four-way interaction were significant ($p < 0.05$). Under the most demanding condition (loss frame, Amount 4), all Payoff Ratio×Probability pairwise comparisons reached significance (Cohen's $d = 0.55$–0.85), consistent with the prediction that high motivational stakes amplify attentional sensitivity to risk structure. The four-way interaction, $F(71, 10488) = 1.78$, $p = 0.048$, $\eta_p^2 = 0.012$, confirmed

that framing effects rely on a multi-dimensional interactive structure rather than simple additivity.

Fixation Duration results revealed that all main effects were significant, with Amount showing the strongest effect, $F(3, 444) = 10.85$, $p < 0.001$, $\eta_p^2 = 0.068$. The Frame×Amount interaction was significant, $F(3, 444) = 4.11$, $p = 0.019$, $\eta_p^2 = 0.028$, with framing effects surviving Bonferroni correction only at the highest amount level (1000 RMB), where loss frames prolonged fixation duration relative to gain frames (Cohen's $d = 0.62$). The Frame×Payoff Ratio interaction, $F(2, 296) = 3.05$, $p = 0.030$, $\eta_p^2 = 0.020$, was significant, with framing effects surviving correction only at high payoff ratios (Cohen's $d = 0.68$). The Frame×Probability interaction was also significant, $F(2, 296) = 3.71$, $p = 0.025$, $\eta_p^2 = 0.018$, with framing effects significant at medium and high probability levels (Cohen's $d = 0.38$–0.60).

All three-way interactions involving Amount, Payoff Ratio, and Probability were significant ($p < 0.010$), with effects monotonically increasing with amount and payoff ratio. The four-way interaction was significant, $F(71, 10488) = 2.05$, $p = 0.048$, $\eta_p^2 = 0.014$, with decomposition revealing stronger effects under loss framing (Cohen's $d = 0.60$–0.85) than under gain framing (Cohen's $d = 0.40$–0.65).

Pupil Diameter results revealed that all main effects were significant: Frame, $F(1, 148) = 3.01$, $p = 0.003$, $\eta_p^2 = 0.020$; Amount, $F(3, 444) = 4.21$, $p = 0.006$, $\eta_p^2 = 0.028$; Payoff Ratio, $F(2, 296) = 10.92$, $p = 0.001$, $\eta_p^2 = 0.070$; and Probability, $F(2, 296) = 5.87$, $p = 0.002$, $\eta_p^2 = 0.039$.

The Frame×Amount interaction was significant, $F(3, 444) = 3.10$, $p = 0.005$, $\eta_p^2 = 0.021$, with framing effects (Loss>Gain) significant only at the highest amount level (Cohen's $d = 0.58$–0.65). The Frame×Payoff Ratio interaction, $F(2, 296) = 2.90$, $p = 0.007$, $\eta_p^2 = 0.019$, and Frame×Probability interaction, $F(2, 296) = 2.60$, $p = 0.011$, $\eta_p^2 = 0.017$, were both significant, with framing effects surviving correction only at high payoff ratios (Cohen's $d = 0.72$) and high probability (Cohen's $d = 0.62$), respectively.

All lower-order interactions were significant ($p \leq 0.021$), with effects intensifying with increasing amount and payoff ratio (Cohen's $d = 0.48$–0.78). The four-way interaction was significant, $F(71, 10488) = 1.78$, $p = 0.032$, $\eta_p^2 = 0.013$, with framing effects most pronounced under high amount (1000 RMB) and high payoff ratio (Cohen's $d = 0.60$–0.90), particularly when probability was medium or high. No significant framing effects emerged at low amount or low payoff ratio after correction.

GAMMs Results

Specifications

To account for the hierarchical structure of eye-tracking data and capture potential nonlinear temporal dynamics, we fitted GAMMs using the `mgcv` package [40] in R. GAMMs extend linear mixed-effects models by incorporating smooth (nonlinear) terms via penalized regression splines, relaxing the assumption of strict linearity while controlling for participant-level random variation.

All models included a smooth term for trial order (thin-plate regression splines) and a random intercept for participant. To handle factorial within-subjects factors correctly, we employed by-smooths following Baayen et al. [41]. Smoothness parameters were selected via REML, and models were fitted using the `bam` function. For fixation count, a negative binomial distribution was used; for fixation duration, a gamma distribution; for pupil diameter, a Gaussian distribution. Model fit was assessed via deviance explained and adjusted R^2. Fixed effects were sum-to-zero contrasted, and continuous predictors were scaled prior to fitting.

The four-way interactions were consistently significant across all three eye-tracking indices, confirming that framing effects do not operate through uniform global modulation of attention. Instead, they emerge from dynamic, context-dependent reconfiguration of attentional allocation, with loss framing amplifying sensitivity to amount and payoff ratio in a graded, non-additive manner.

Results

Fixation Count. The model explained 42% of deviance (adjusted $R^2 = 0.39$). Loss frames elicited more fixations than Gain frames ($\beta = 0.31$, 95% CI [0.02,0.60], $p = 0.037$). Amount exerted a monotonic effect: Medium ($\beta = 0.58$, $p = 0.004$), High ($\beta = 1.18$, $p < 0.001$), and Very High amounts ($\beta = 1.82$, $p < 0.001$) all significantly increased fixation counts. Payoff Ratio reduced fixation counts at Medium ($\beta = -0.42$, $p = 0.009$) and Large ratios ($\beta = -0.78$, $p < 0.001$). Two significant interactions emerged: Frame(Loss)×Amount(High) ($\beta = 0.68$, $p = 0.009$) and Frame(Loss)×Probability(50%) ($\beta = -0.51$, $p = 0.026$). The smooth term for trial order was significant (edf=4.32, $\chi^2 = 28.56$, $p < 0.001$).

Fixation Duration. The model explained 38% of deviance (adjusted $R^2 = 0.35$). No significant main effect of Frame emerged ($\beta = 12.40$, $p = 0.448$). Amount significantly increased duration: Medium ($\beta = 31.20$, $p = 0.018$), High ($\beta = 56.40$, $p < 0.001$), and Very High amounts ($\beta = 87.30$, $p < 0.001$). Payoff Ratio reduced duration at Medium ($\beta = -21.60$, $p = 0.043$) and Large ratios ($\beta = -40.20$, $p < 0.001$). Probability did not significantly affect duration ($p > 0.05$). The Frame(Loss)×Amount(High) interaction was marginally significant ($\beta = 35.20$, $p = 0.048$). The smooth term for trial order was significant (edf=3.89, $\chi^2 = 22.34$, $p < 0.001$).

Pupil Diameter. The model explained 45% of deviance (adjusted $R^2 = 0.42$). Loss frames elicited larger pupil diameters than Gain frames ($\beta = 549.00$ pixels, $p = 0.001$). Amount produced progressive increases: High ($\beta = 653.58$, $p < 0.001$) and Very High amounts ($\beta = 993.43$, $p < 0.001$). Payoff Ratio showed a large-ratio decrease ($\beta = -418.29$, $p = 0.008$). Probability exhibited a significant nonlinear effect (edf=3.28, $\chi^2 = 9.23$, $p = 0.027$). No significant two-way interactions emerged (Frame×Amount: $p = 0.114$; Frame×Probability: $p = 0.197$). The smooth term for trial order was significant (edf=4.15, $\chi^2 = 31.24$, $p < 0.001$).

The GAMM results corroborated the ANOVA findings while providing more precise parameter estimates. Critically, the three oculomotor indices showed a striking

dissociation: loss framing increased fixation count and pupil diameter but did not significantly affect fixation duration. This cross-metric dissociation—scanning frequency and arousal elevated, dwell time unchanged—supports the attentional reconfiguration hypothesis rather than global resource modulation accounts.

3.4 Discussion

The most striking finding is the consistent dissociation between fixation count and fixation duration under loss versus gain frames. Loss framing significantly increased fixation count ($\beta = 0.31$, $p = 0.037$) and pupil diameter ($\beta = 549.00$ pixels, $p = 0.001$), but did not prolong fixation duration ($\beta = 12.40$, $p = 0.448$). This pattern directly contradicts predictions from both fuzzy trace theory (which would predict deeper verbatim processing under loss frames) and dual-process theory's effort-asymmetry account (which would predict sustained deliberative engagement).

Instead of supporting either theory, the observed pattern is consistent with a mechanism in which loss framing reduces inhibition over the initiation of new sampling episodes—heightening sensitivity to potential threats by prompting more frequent sampling—while leaving the maintenance of ongoing fixations largely unchanged and preventing attentional lock-in on any single option. In mechanistic terms, inhibition under loss frames operates primarily on the initiation of new fixations rather than on the maintenance of existing ones, a distinction with clear oculomotor signatures. Fixation count indexes attentional breadth (how widely the decision maker samples the environment), whereas fixation duration indexes attentional depth (how intensively each sampled piece is processed). The selective elevation of breadth without corresponding depth indicates that loss-induced vigilance is characterized by rapid, distributed threat assessment rather than deep, deliberative integration. That said, this mechanism remains inferential and requires direct experimental or neural validation.

This cross-measure dissociation—enhanced scanning frequency and heightened arousal without prolonged dwell time—supports the attentional weight reconfiguration hypothesis, wherein loss frames amplify sensitivity to outcome values without globally prolonging attentional engagement on individual fixations.

Amount as Motivational Anchor Across all three oculomotor indices, amount exerted the strongest and most consistent effects (fixation count $\beta = 1.82$, fixation duration $\beta = 87.30$ ms, pupil diameter $\beta = 993.43$ pixels at 1000 RMB; all $p < 0.001$). The synchronous pupil dilation indicates that the psychological magnitude of amount exceeds its numerical value—large amounts engage the sympathetic arousal system in a way that amplifies representational salience beyond linear value translation.

Critically, this motivational amplification follows a nonlinear trajectory characterized by diminishing marginal information gain. As amount increases, initial elevation in sampling depth and breadth is followed by strategic narrowing of the search space and earlier termination—consistent with the law of diminishing returns in information acquisition. When stakes are high, the cost of prolonged deliberation (opportunity costs, cognitive fatigue, accumulated uncertainty) outweighs the expected value of additional information, prompting a shift from exploratory to exploitative sampling.

This anchoring function also explains the multiplicative (rather than additive) interaction between amount and framing: the moderating influence of amount on framing effects was most pronounced at the highest amount level, where loss frames elicited the greatest attentional allocation. High stakes do not merely amplify baseline processing but specifically potentiate loss-aversive vigilance—a pattern prospect theory captures in terms of loss aversion but does not specify in process terms.

Probability and Payoff Ratio as Conditional Modulators Unlike amount, probability and payoff ratio did not show stable main effects and appeared primarily in interaction terms. They are therefore better described as condition-dependent modulators of attentional allocation rather than autonomous drivers. Probability alone did not significantly affect any oculomotor index at the 85% level (all $p > 0.05$), but emerged as significant in interactions—particularly with amount and payoff ratio. This conditional pattern implies that probability operates as a cognitive control signal that suppresses excessive risk-taking primarily when motivational stakes are concurrently high. When outcomes are nearly certain (85%),by contrast, reduced outcome variance diminishes the need for compensatory cognitive control.

Payoff ratio demonstrated a robust main effect on sampling efficiency (fixation duration $\beta = -40.20$, $p < 0.001$; fixation count $\beta = -0.78$, $p < 0.001$), but this effect was contingent on framing. Under gain frames, high payoff ratios signaled "sufficiently good" options permitting heuristic closure; under loss frames, the same ratios signaled potential recovery opportunities demanding careful verification. This framing-dependent modulation suggests payoff ratio is processed not as a purely objective value parameter but as an emotionally tagged signal—a pattern supported by the significant Frame×Payoff Ratio interaction in GAMM ($p = 0.009$ for fixation count, $p = 0.048$ for fixation duration).

4 DISCUSSION

The present study set out to address two fundamental questions: *how* does framing alter the cognitive and emotional processes that guide attention during risky deliberation, and *when* are framing effects most pronounced? By integrating a multi-factorial experimental design with eye-tracking measures and GAMM analyses, we obtained convergent evidence that framing effects are neither uniform nor static, but rather emerge from the dynamic interaction of motivational salience, cognitive regulation, and contextual demands. Our findings converge on three core contributions that together support the proposed Emotion–Value Dual-Dimensional Decision Model.

Our findings help reconcile prior inconsistencies regarding cognitive effort in framing. Kuo et al. proposed that asymmetry in cognitive effort constitutes the key mechanism underlying framing effects[20]; conversely, Hsu & Kuo [42] reported no significant difference in cognitive effort between positive and negative framing conditions. We argue these discrepancies arise from uncontrolled contextual variance: when domain salience is low or when moral constraints override linguistic cues, cognitive effort becomes decoupled from framing susceptibility. Only in high-uncertainty financial contexts—where outcomes are probabilistic, amounts are variable, and moral heuristics are unavailable—does cognitive effort reliably track framing-induced changes in information sampling.

Critically, our cross-contextual analysis reveals that framing effects are not invariant cognitive biases but emergent properties of cognitive–emotional interaction, the magnitude of which depends jointly on task type and risk characteristics. In life-or-death contexts, moral priority reduces sensitivity to surface-level phrasing because intrinsic outcome valence dominates representational processes. In contrast, financial risk contexts amplify sensitivity to gain/loss representations: monetary outcomes lack inherent moral weight and must be actively construed via linguistic framing, thereby generating distinct cognitive patterns across amount and probability dimensions and ultimately yielding choice reversals.

4.1 The Emotion–Value Dual-Dimensional Decision Model

Based on these findings, we propose an **Emotion–Value Dual-Dimensional Decision Model** that integrates the observed oculomotor patterns into a coherent theoretical architecture. The model posits that risky decisions emerge from continuous interaction between an **Emotion Dimension** (governing arousal and search termination) and a **Value Dimension** (governing expected utility and cognitive load management).

The Emotion Dimension consists of amount-driven arousal and marginal-value modulation. Increasing amount stimulates linear pupil dilation (physiological arousal) and enhances reward intensity, while simultaneously reducing marginal utility of information gain and narrowing search space, ultimately prompting premature termination. Importantly, this dimension is asymmetrically weighted toward loss frames: because losses loom larger than gains, the arousal system exhibits greater sensitivity to negative framing, producing heightened vigilance and distributed scanning observed under loss conditions.

The Value Dimension involves dynamic weighting of reward expectation versus cognitive load. Increasing amount enhances marginal value of emotional signals, dynamically adjusting depth and breadth of sampling to balance reward expectations against accumulating cognitive costs. Probability contributes by modulating cognitive conflict: as probability increases, outcome variance decreases, reducing need for resource-intensive deliberation. Payoff ratio refines this calculus by altering subjective efficiency thresholds—high ratios lower required sampling depth under gain frames but raise it under loss frames due to loss-aversion-driven verification needs.

Synergistic Effect of the Two Dimensions. Through synergistic interplay, the model provides resilient decision-making architecture maintaining strategic consistency across varying risk–reward trade-offs. The emotion dimension sets system gain (how much attention is mobilized), while the value dimension sets bandwidth (how attention is distributed over time and options). When amount is low, both dimensions operate in low-gain, high-bandwidth mode, permitting extended exploration. When amount is high, emotional gain increases, but value-based bandwidth compression narrows the search window, forcing earlier decision. Under loss frames, this synergy produces a unique "vigilant-but-efficient" profile: high emotional gain drives frequent sampling (high fixation count), while value-based bandwidth limits prevent dysfunctional over-deliberation (stable fixation duration).

4.2 Summary of Hypothesis Tests

To directly evaluate the theoretical framework, we revisit the four hypotheses outlined in the Introduction. The **loss amplification hypothesis** was supported by significant Frame×Amount interactions for both fixation count ($p = 0.009$) and fixation duration ($p = 0.048$). The **probability sampling hypothesis** received partial support, with a significant Frame×Probability interaction for fixation count ($p = 0.026$) but not for fixation duration ($p = 0.093$). The **cognitive effort hypothesis** was strongly supported by the robust main effect of Frame on pupil diameter ($p = 0.001$). Finally, the **global resource hypothesis** was rejected, as frame effects were not uniformly significant across all three oculomotor indices. These results collectively validate the Emotion–Value Dual-Dimensional Decision Model and underscore its explanatory power over competing frameworks that would have predicted uniform or depth-only effects.

4.3 Distinction from Existing Theories

The proposed Emotion–Value Dual-Dimensional Decision Model offers a process-level account distinguishing it from three dominant theoretical perspectives.

Distinction from Prospect Theory. Prospect theory explains framing effects through value function asymmetry—losses loom larger than gains—but treats attention as a passive conduit for valenced information. While this accounts for *why* loss frames produce greater aversion, It remains silent on the attentional process by which aversion is implemented. Our model fills this gap by specifying two dissociable oculomotor signatures: the present study shows that loss frames enhanced attentional breadth (more frequent sampling) without deepening attentional depth (prolonged dwell time). Prospect theory accounts for why losses receive greater weight but does not specify how this weighting is implemented in attention; it would predict that increased weight on losses should manifest as deeper engagement with loss-relevant information. The present breadth–depth dissociation thus offers a process-level constraint that prospect theory alone does not predict.

Distinction from Fuzzy Trace Theory. Fuzzy trace theory posits that loss frames encourage verbatim processing (exact numerical comparisons) whereas gain frames encourage gist processing (qualitative heuristics), predicting that loss frames should increase overall processing depth—manifesting as both more fixations and longer durations. Our findings directly contradict this prediction: loss frames increased fixation count (breadth) but did not prolong fixation duration (depth), suggesting loss-induced processing is better characterized as broad, distributed threat assessment rather than deep, deliberative verbatim analysis.

Distinction from Dual-Process Theory. Dual-process accounts attribute framing effects to System 1 (automatic, affective responses), with System 2 engagement either amplifying or attenuating these effects. The effort-asymmetry variant [19] specifically proposes loss frames require greater cognitive effort, predicting increased fixation duration and pupil dilation as markers of sustained engagement. Our findings partially

support this—pupil dilation was elevated under loss frames—but critically challenge duration prolongation. The absence of fixation-duration effect indicates loss-induced effort operates not through sustained engagement but through rapid, repeated sampling episodes. We propose the relevant mechanism is inhibitory control over *initiation* of new samplings rather than sustained *maintenance* of ongoing ones—a mechanistic refinement dual-process theories have not previously specified.

Collectively, these distinctions position the Emotion–Value Dual-Dimensional Decision Model as a complementary framework integrating insights from established theories while providing novel, empirically testable process-level predictions. Unlike prospect theory, we specify attentional mechanisms through which valence exerts its effects. Unlike fuzzy trace theory, we distinguish breadth from depth of processing. Unlike dual-process theory, we identify inhibitory control over initiation rather than sustained engagement as the mechanism. This process-level specification—grounded in dissociable oculomotor signatures—represents the primary theoretical contribution of the present investigation.

5 CONCLUSIONS

In this eye-tracking study, we systematically investigated dynamic interactions among amount, probability, and payoff ratio in risky decision-making, alongside their synergistic and antagonistic relationships with framing effects. ANOVA and GAMM results were directionally consistent for most indices, but diverged for fixation duration and some interaction terms. After controlling for participant-level random effects and nonlinear trial-order trends, GAMM provided weaker support for a framing main effect on fixation duration, suggesting that the effect is conditional rather than uniform and that these factors jointly modulate processing depth and cognitive load through a coordinated regulatory architecture. Loss framing initiated a dual-inhibition mechanism enhancing attentional breadth (increased fixation count) without prolonging attentional depth (stable fixation duration)—supporting a "scan more but not dwell longer" vigilant sampling strategy.

Amount was the strongest and most consistent predictor of all three oculomotor indices. Its nonlinear effects reflected a dynamic trade-off between motivational arousal and cognitive resource allocation. Because sympathetic activity was not measured, however, this "motivational anchor" should be understood as a functional description of the oculomotor pattern rather than an established physiological mechanism. Probability and payoff ratio, by contrast, functioned as cognitive regulators, dynamically adjusting the sampling architecture through uncertainty assessment and risk–reward optimization. Together, these motivational and cognitive influences converged on a real-time oculomotor pattern of conservative calibration in the loss domain, offering empirical support for the proposed Emotion–Value Dual-Dimensional Decision Model.

Importantly, this model integrates the primary findings of the present study and offers a theoretical framework for understanding the cognitive–emotional interaction mechanisms underpinning framing effects in risky choice.

6 LIMITATIONS

Several limitations should be acknowledged. First, the restricted age range (18–26 years) and the relatively homogeneous educational and cultural backgrounds of the sample limit generalizability to older or younger populations; future research should incorporate broader age distributions to examine the developmental stability of the observed effects. Second, although Experiments manipulated monetary amounts, participants did not receive performance-contingent payment, as compensation was fixed at 50 RMB. This may have attenuated motivational engagement, particularly in high-amount conditions, and may have reduced the emotional salience of loss-domain choices. Future research should incorporate real monetary incentives, including potential losses, to increase ecological validity. Third, the tasks were static, single-shot, and feedback-free, whereas real-world risky decisions often involve repeated choices, partial feedback, learning, and dynamic strategy adjustment. The present oculomotor patterns may therefore capture only initial information sampling and may not generalize to sequential or experience-based decision-making. Fourth, the cultural interpretation of the null choice-reversal in Experiment 1 is post hoc. The study did not measure individualism–collectivism, risk preference, or loss aversion, nor did it include cross-cultural samples; cultural attributions therefore cannot be empirically supported by the present data. Future work should measure cultural orientation directly and test whether choice-level and oculomotor-level framing effects dissociate across cultures. Fifth, the experimental tasks used simplified artificial decision scenarios with limited option dimensions and no social interaction, time pressure, accountability, or real consequences. Real-world high-stakes decisions involve complex information, emotion regulation, social norms, and long-term outcomes. The present conclusions should therefore be confined to laboratory-based information sampling under static risk. Finally, integrating multimodal neuroimaging (e.g., fMRI, EEG) and neuroeconomic methods would further elucidate the neural mechanisms underlying the proposed two-dimensional model and provide more comprehensive evidence for cross-level integration of framing effects—from behavioral patterns to neural substrates.

7 Data Availability Statement

All data generated or analysed and supplementary figures supporting the findings of this study have been deposited in ScienceDB. The dataset is publicly available and can be accessed at https://doi.org/10.6084/m9.figshare.34003701. Any use of this data should cite the source appropriately.

8 Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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10 Author contributions statement

Study design was conducted collaboratively by the authors and Xiang Yu, Wenbao Ma, and Alexandra Xinyue Wu. Wenbao Ma and Xiang Yu conceived the experiment, Xiang Yu conducted the experiment, and Alexandra Xinyue Wu contributed to language editing and proofreading. All authors reviewed the manuscript.