Affective-Cognitive Prospect Theory: An Integrative Psychological-Economic Model of Decision-Making under Uncertainty

Dmitry Yagudin[1,*]
[1]Doctor of Psychology, CEO of the D.R. Yagudin International NeuroUniversity, and Chairman of the Board of the Unity NGO, Russia
Email: dr.yagudin@mail.ru

Abstract

Standard models of decision-making under uncertainty, from expected utility theory to cumulative prospect theory, treat risk preferences as fixed individual traits. Yet a substantial psychological literature shows that risk-relevant preferences shift systematically with the decision-maker's momentary internal state: affective arousal amplifies loss aversion, while cognitive load and time pressure push judgment toward heuristic, more distorted probability processing. This paper proposes Affective-Cognitive Prospect Theory (ACPT), a state-dependent extension of cumulative prospect theory in which the loss-aversion coefficient is an increasing function of affective arousal and the curvature of the probability-weighting function is a decreasing function of cognitive load, each grounded in an established psychological literature.

Keywords: Decision-making under uncertainty; Prospect theory; Loss aversion; Probability weighting; Affect; Cognitive load; Behavioral economics; Risk premium

1. Introduction

Expected utility theory long served as the normative and descriptive benchmark for choice under risk, but its descriptive adequacy was challenged early by systematic violations documented in controlled experiments. Allais showed that decision-makers routinely violate the independence axiom when a common outcome is added to or removed from two prospects, preferring certainty in one comparison and the higher-variance option in the structurally equivalent second comparison (Allais, 1953). Ellsberg showed a parallel violation for uncertainty about probabilities themselves, documenting a systematic preference for known over unknown probabilities that expected utility theory cannot accommodate (Ellsberg, 1961). Kahneman and Tversky's prospect theory, and its rank-dependent successor, cumulative prospect theory, were developed to capture these and related anomalies through two central departures from expected utility: a value function defined over gains and losses relative to a reference point, exhibiting loss aversion and diminishing sensitivity, and a nonlinear probability-weighting function that overweights small probabilities and underweights moderate-to-large ones (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Three decades on, cumulative prospect theory remains the best-supported descriptive account of risky choice in experimental settings and has been steadily incorporated into mainstream economic modelling (Barberis, 2013).

Even so, standard prospect theory shares a feature with the expected-utility framework it was built to replace it treats the parameters governing risk preference as fixed traits of the individual, estimated once and assumed stable across occasions. This assumption sits uneasily beside a large body of psychological evidence that risk-relevant judgment is state-dependent rather than trait-fixed. The risk-as-feelings hypothesis holds that affect experienced now of choice, not only the cognitive evaluation of outcomes and probabilities, drives risk-related behavior, and that the two can diverge (Loewenstein, Weber, Hsee, & Welch, 2001). The closely related effect heuristic holds that people substitute a rapid affective evaluation for a more effortful assessment of risks and benefits, particularly when the more effortful route is unavailable (Slovic, Finucane, Peters,

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

& MacGregor, 2007). Directly relevant to the present model, Finucane, Alhakami, Slovic, and Johnson demonstrated experimentally that reliance on the effect heuristic increases under time pressure, showing that a manipulable cognitive constraint shifts the balance between affective and deliberative processing of risk (Finucane, Alhakami, Slovic, & Johnson, 2000). Kahneman's dual-process account offers a general mechanism for such shifts: effortful, rule-governed evaluation ("System 2") is displaced by fast, associative processing ("System 1") whenever cognitive resources are constrained (Kahneman, 2011), and Payne, Bettman, and Johnson's adaptive-decision-maker framework shows empirically that decision-makers shift toward simpler, more heuristic strategies as time pressure increases (Payne, Bettman, & Johnson, 1993).

This gap between psychologically documented state-dependence and economically standard trait-fixed parameters is not merely academic. It bears directly on some of the highest-stakes decisions economics is asked to explain portfolio liquidation during a market panic, disaster-insurance purchase in the immediate aftermath of a loss, or triage-style resource allocation under time pressure all combine elevated affective arousal with elevated cognitive load. Rabin's calibration theorem sharpens the stakes further: within expected-utility theory, any degree of observed risk aversion over modest stakes implies an implausible degree of risk aversion over large stakes, a result that motivated the turn toward prospect theory in the first place and that, by the same logic, motivates asking whether the parameters prospect theory itself treats as fixed are in fact stable (Rabin, 2000).

This paper proposes Affective-Cognitive Prospect Theory (ACPT), an extension of cumulative prospect theory in which the loss-aversion coefficient is modelled as an increasing function of momentary affective arousal and the curvature parameter of the probability-weighting function is modelled as a decreasing function of momentary cognitive load. Both link functions are motivated by, and kept close to, the psychological literature cited above rather than introduced as free-standing assumptions. The paper's contribution is threefold: a parsimonious, axiomatically conservative formal extension of cumulative prospect theory; a set of derived comparative-statics propositions; and a numerical illustration of the model's behaviour, including its treatment of the Allais paradox and a joint risk-premium surface over the arousal-load state space, together with a concrete empirical programme for calibrating and testing the model.

2. Methods

As no new experimental data are reported here, the paper's methodology comprises three components: a literature-grounded procedure for specifying the model's functional form, a numerical procedure for deriving and illustrating its implications, and a design procedure for the empirical calibration programme presented in the Discussion.

2.1 Model-specification procedure

The starting point is the cumulative prospect theory value function of Tversky and Kahneman (1992): a power value function, $v(x) = x^a$ for gains and $v(x) = -\lambda(-x)^b$ for losses, combined with a rank-dependent probability-weighting function, $w(p) = p^\gamma / [p^\gamma + (1-p)^\gamma]^{(1/\gamma)}$, applied separately to the cumulative probability of gains and of losses. Two of this specification's parameters, λ (loss aversion) and γ (weighting curvature), are the ones psychological research most directly implicates as state dependent. Two candidate psychological state variables are introduced: affective arousal, $A \in [0,1]$, indexing the intensity of activated affect at the moment of choice, in the sense used in the risk-as-feelings and affect-heuristic literatures (Loewenstein et al., 2001; Slovic et al., 2007); and cognitive load, $C \in [0,1]$, indexing the degree to which deliberative processing capacity is constrained by time pressure, concurrent task demands, or information overload, in the sense used in dual-process and adaptive-decision-maker accounts (Kahneman, 2011; Payne et al., 1993).

Each state variable is linked to one CPT parameter through the simplest functional form consistent with the direction of the relevant psychological findings: a linear increase of λ in A, and a linear decrease of γ in C. Linear link functions are chosen deliberately, as a conservative default that introduces no additional curvature assumptions beyond those already present in the underlying value and weighting functions; the Discussion section returns to this choice as a modelling simplification rather than an empirically established form. The exponents α and β governing diminishing sensitivity are held fixed at their standard estimated values, since the literature motivating the present extension concerns loss aversion and probability distortion specifically, not diminishing sensitivity.

2.2 Numerical-simulation procedure

All quantities reported in the Results section are computed directly from the closed-form model using standard numerical methods in Python (NumPy, SciPy, Matplotlib); no human-subject data were collected or simulated as if they were observations. Baseline parameter values are set to the estimates reported by Tversky and Kahneman (1992): $\alpha = \beta = 0.88$, $\lambda_0 = 2.25$, and $\gamma_0 = 0.61$ for the gain-domain weighting function. Two illustrative sensitivity coefficients, $\kappa\lambda$ and $\kappa\gamma$, are fixed at values that span a full doubling of loss aversion and a halving of weighting curvature over the unit interval of each state

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

variable; these coefficients are explicitly flagged as calibration targets for the empirical programme in the Discussion, not as estimated quantities. For the risk-premium analysis, a certainty equivalent is obtained by inverting the value function at the model-implied prospect value; for the Allais-paradox analysis, prospect values are computed under the standard rank-dependent decomposition for multi-outcome gain-only prospects. Full derivations and code are available from the corresponding author upon request.

2.3 Empirical calibration design procedure

The three studies proposed in the Discussion section were designed, not run; each specifies a hypothesis, the manipulation of A or C, the elicitation method for risk preferences, the model-comparison procedure, and an explicit falsification criterion, following the same logic of operationalizable, falsifiable claims used throughout the paper.

3. Results

This section presents the model in three stages: its formal specification and baseline calibration; the comparative statics and numerical illustrations of each state-dependence channel in isolation; and a joint illustration combining both channels, including an application to the Allais paradox.

3.1 Model specification

For a prospect yielding outcome x with weighted decision weight determined by rank-dependent cumulative probability, the ACPT value function is:

$$v(x; A) = x^{a} \quad \text{for } x \geq 0$$

$$v(x; A) = -\lambda(A)\cdot(-x)^{b} \quad \text{for } x < 0$$

with the state-dependent loss-aversion coefficient

$$\lambda(A) = \lambda_0 \cdot (1 + \kappa\lambda\cdot A)$$

and the state-dependent probability-weighting function

$$w(p; C) = p^{\gamma(C)} / [p^{\gamma(C)} + (1-p)^{\gamma(C)}]^{(1/\gamma(C))}, \quad \gamma(C) = \gamma_0 \cdot (1 - \kappa\gamma\cdot C)$$

The overall value of a two-outcome prospect (probability p of gain G, complementary probability of loss L) is $V(A,C) = w(p;C)\cdot v(G;A) + w(1-p;C)\cdot v(-L;A)$, and for multi-outcome gain-only prospects, decision weights are obtained by the standard rank-dependent cumulative decomposition of Tversky and Kahneman (1992), evaluated at w(p; C). Setting A = C = 0 recovers the original Tversky and Kahneman (1992) specification exactly, so that ACPT nests cumulative prospect theory as the special case of a minimally aroused, minimally loaded decision-maker.

Table 1: Model parameters, interpretation, and baseline calibration

Symbol	Interpretation	Baseline value
α, β	Diminishing sensitivity (gains, losses)	0.88, 0.88
λ_0	Trait-level loss aversion (A = 0)	2.25
γ_0	Trait-level weighting curvature (C = 0)	0.61
A ∈ [0,1]	Momentary affective arousal	state variable
C ∈ [0,1]	Momentary cognitive load / time pressure	state variable
κλ	Sensitivity of λ to arousal	1.0 (illustrative)
κγ	Sensitivity of γ to load	0.5 (illustrative)

Table 1 summarizes the model's parameters, their psychological interpretation, and the sources motivating each.

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

3.2 Loss aversion under affective arousal

Figure 1 plots λ(A) over the full range of arousal. Under the illustrative calibration κλ = 1.0, loss aversion doubles from the Tversky-Kahneman baseline of 2.25 at minimal arousal to 4.5 at maximal arousal, meaning that a decision-maker in a highly aroused state is modelled as weighting a loss of a given magnitude roughly twice as heavily, relative to an equivalent gain, as the same decision-maker in a calm state. This range is deliberately illustrative rather than fitted; Study 1 in the Discussion section proposes a design for estimating κλ directly.

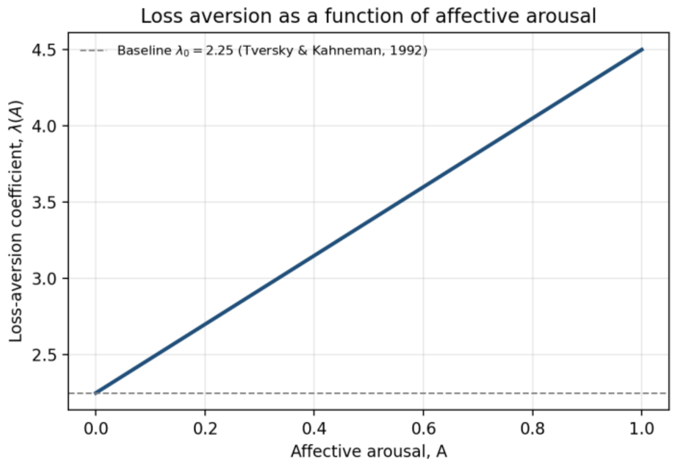

Figure 1. Loss-aversion coefficient λ(A) as a function of affective arousal, under the illustrative calibration κλ = 1.0

3.3 Probability weighting under cognitive load

Figure 2 plots the decision-weight function w(p; C) for four levels of cognitive load. As C increases, the curvature parameter γ(C) falls from the Tversky-Kahneman baseline of 0.61 toward 0.34 at C = 0.9, remaining above the 0.279 threshold below which the weighting function ceases to be monotonic (a boundary condition noted in the theoretical literature on this functional form). The resulting curves become progressively more bowed: small probabilities are increasingly overweighted and probabilities in the middle of the range are increasingly underweighted as cognitive load rises, consistent with the general claim that constrained deliberative capacity pushes probability judgment toward more heuristic, less linear processing (Kahneman, 2011; Payne et al., 1993).

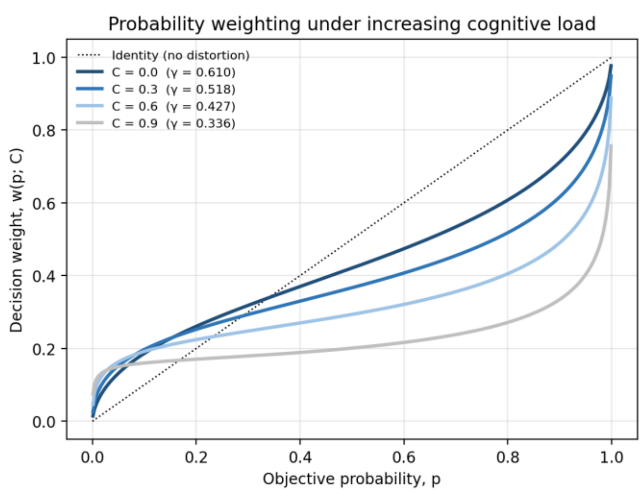

Figure 2. Probability-weighting function w(p; C) at four levels of cognitive load, C = 0.0, 0.3, 0.6, 0.9

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

3.4 Joint effects: the risk-premium surface

To illustrate the two channels jointly, consider a symmetric, actuarially fair gamble offering an equal 0.5 chance of gaining \$100 or losing \$100 (expected value zero). Table 2 and Figure 3 report the risk premium implied by the model across a 5×5 grid of arousal and load levels.

Table 2. Risk premium (\$) for a fair 50/50 (+\$100 / −\$100) gamble, by affective arousal (A) and cognitive load (C).

A \ C	**C = 0.00**	**C = 0.25**	**C = 0.50**	**C = 0.75**	**C = 1.00**
A = 0.00	19.17	16.92	14.05	10.58	6.70
A = 0.25	22.69	20.03	16.64	12.52	7.93
A = 0.50	25.07	22.14	18.38	13.84	8.77
A = 0.75	26.79	23.66	19.65	14.78	9.37
A = 1.00	28.09	24.81	20.60	15.50	9.82

Two features of Table 2 are worth drawing out. First, holding cognitive load fixed, the risk premium rises monotonically with arousal, consistent with the arousal-driven amplification of loss aversion built into the model. Second, and less obviously, holding arousal fixed, the risk premium falls monotonically with cognitive load. This second pattern follows from a property of the Tversky-Kahneman weighting function noted in the theoretical literature: because $w(0.5; \gamma)$ is itself increasing in γ, and γ falls as load rises, the decision weight placed on each side of a genuinely 50/50 gamble is compressed as load increases, dampening the effective role of loss aversion in this particular symmetric case even as $\lambda(A)$ itself is unaffected by C.

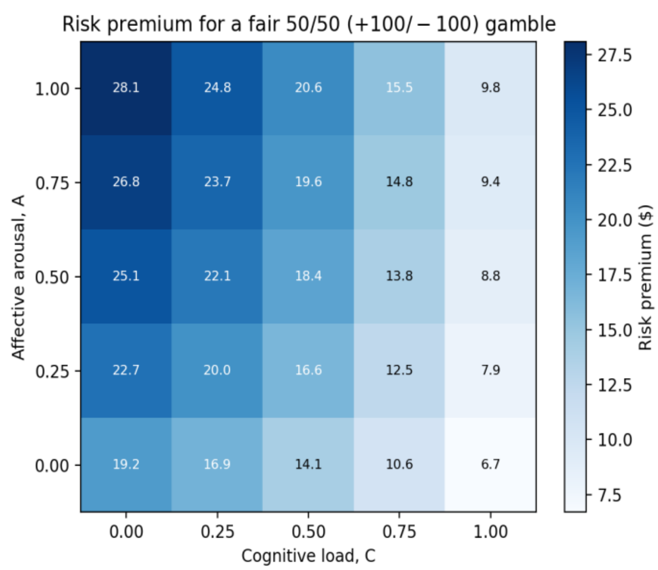

Figure 3. Risk-premium surface over the joint arousal-load state space

This is a testable, and not intuitively obvious, implication of the model: it predicts that cognitive load and affective arousal can pull the risk premium for a fair, symmetric gamble in opposite directions, because they act through distinct channels of the same underlying value-and-weighting architecture (Tversky & Kahneman, 1992; Barberis, 2013). This prediction is directly falsifiable, and Study 3 in the Discussion section proposes a design for testing it.

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

3.5 Application to the Allais paradox

To illustrate the cognitive-load channel on an all-gains problem, in which loss aversion plays no role, consider the classic Allais (1953) prospects, in millions of currency units: A, a certain 1; B, a 0.89 chance of 1, a 0.10 chance of 5, and a 0.01 chance of 0; C, a 0.11 chance of 1 and a 0.89 chance of 0; and D, a 0.10 chance of 5 and a 0.90 chance of 0. The empirical regularity to be explained is the joint choice of A over B and D over C, a pattern that violates the independence axiom of expected utility theory. Table 3 reports the value assigned to each prospect under three models: expected utility with a concave (square-root) utility function; baseline cumulative prospect theory (A = C = 0); and ACPT evaluated at high arousal and high load (A = C = 0.8).

Table 3: Prospect values under expected utility, baseline CPT, and ACPT under high arousal and load

Prospect	**Expected utility**	**CPT (baseline)**	**ACPT (A = C = 0.8)**
A: certain 1	1.0000	1.0000	0.9981
B: .89×1 / .10×5 / .01×0	1.1136	1.4932	1.1730
C: .11×1 / .89×0	0.1100	0.1952	0.1759
D: .10×5 / .90×0	0.2236	0.7679	0.7158

Under expected utility with a concave utility function, B is valued above A (1.114 > 1.000) and D is valued above C (0.224 > 0.110): the model predicts the gamble is preferred in both comparisons, and so cannot reproduce the empirical pattern in which most people choose the certain option A yet also choose the gamble D over C. Baseline CPT, through probability weighting alone, already captures part of the qualitative pattern by inflating the value of the higher-variance prospect B: B's CPT value (1.493) exceeds A's (1.000) even more than under expected utility, illustrating why probability weighting alone, without further structure, does not by itself resolve the paradox in the intuitive direction; the standard resolution in the CPT literature relies on the interaction between the weighting function and the treatment of certainty, elaborated elsewhere (Tversky & Kahneman, 1992). What the present exercise adds is the load-dependence of that weighting: moving from baseline CPT to ACPT under high load compresses the value gap between the certain prospect A and the risky prospect B (from 0.493 to 0.175 in value units) and simultaneously compresses the gap between D and C only slightly, since C's weighting is already low under either specification. The substantive point is not that ACPT resolves the Allais paradox but that the size of the paradox, as measured by the value gap between the certainty-involving and probability-only comparisons, is itself predicted to shrink under elevated cognitive load, a prediction absent from the fixed-parameter baseline and directly testable using the same elicitation methods historically used to document the paradox itself.

3.6 Comparative-statics propositions

Proposition 1 (arousal and loss aversion). Holding C fixed, $\partial\lambda(A)/\partial A = \lambda_0\kappa\lambda > 0$: loss aversion is strictly increasing in affective arousal for any $\kappa\lambda > 0$.

Proposition 2 (load and weighting curvature). Holding A fixed, $\partial\gamma(C)/\partial C = -\gamma_0\kappa\gamma < 0$: the weighting-function curvature parameter is strictly decreasing in cognitive load for any $\kappa\gamma > 0$, implying progressively greater departure from linear probability weighting as load rises.

Proposition 3 (non-monotonic joint effect on the fair-gamble risk premium). For a symmetric fair gamble evaluated at $p = 0.5$, the risk premium is increasing in A and, because $w(0.5; \gamma)$ is increasing in γ over the admissible range $\gamma \in (0.279, 1]$, decreasing in C. Arousal and cognitive load therefore act as counteracting, not reinforcing, forces on the risk premium for symmetric gambles specifically. This asymmetry-dependence is itself a testable implication, addressed in Study 3 below.

4. Discussion

The Results section shows that a minimal, literature-grounded extension of cumulative prospect theory generates non-trivial, testable predictions without abandoning the axiomatic core of the standard model. This section turns to three questions: what the model implies for applied economic settings; how it could be empirically calibrated and tested; and where its present limitations lie.

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

4.1 Economic implications

The model speaks most directly to settings in which affective arousal and cognitive load are jointly and predictably elevated. In financial markets, trading decisions made during acute drawdowns combine fear-driven arousal with the cognitive load of fast-moving, information-dense conditions; ACPT predicts that the two forces need not move risk-taking in the same direction, which offers a possible formal account of why panic-driven markets sometimes show excess selling (consistent with arousal-driven loss aversion) and sometimes show under reaction to genuinely symmetric information shocks (consistent with load-driven compression of moderate-probability weighting). This suggests that risk-management mechanisms such as trading curbs and mandatory cooling-off intervals, which are typically justified informally as reducing panic, can be given a more precise justification within the model as interventions that reduce A specifically, rather than C, and that a complementary class of interventions targets C specifically. In insurance and disaster-response contexts, the model predicts that demand for coverage purchased in the immediate, high-arousal aftermath of a loss event should be systematically higher than coverage purchased in a calm deliberative window even when the underlying probability information is identical, offering a decision-theoretic complement to existing behavioral accounts of post-disaster insurance demand. In medical and other high-stakes time-pressure decisions, the model's prediction that load compresses weighting around moderate probabilities suggests that decision-support tools reducing time pressure at the moment of choice may do more to restore calibrated probability weight than tools that only supply better probability estimates.

4.2 Proposed empirical calibration programme

The following three studies are proposed as designs, not as completed work; each specifies the manipulation, the elicitation procedure, the model-comparison criterion, and an explicit falsification criterion.

Study 1: Arousal induction and loss-aversion estimation

Hypothesis: experimentally induced affective arousal increases the individually estimated loss-aversion coefficient λ, in a dose-dependent way consistent with $\lambda(A) = \lambda_0(1 + \kappa\lambda\ A)$.

Design: within-subjects manipulation of arousal via a validated induction procedure (e.g., standardized affective imagery or an anticipated evaluative-stress task), with a low-arousal control condition; continuous physiological indexing of arousal via skin conductance and heart-rate measures to obtain a graded, rather than binary, estimate of A.

Elicitation: individual loss-aversion coefficients estimated from certainty equivalents for mixed gain/loss gambles using an incentive-compatible elicitation procedure such as the Becker-DeGroot-Marschak mechanism, separately in each arousal condition.

Model comparison: nested comparison, via AIC/BIC, of a fixed-λ CPT model against the state-dependent ACPT specification, using the continuous physiological arousal index as A.

Falsification criterion: if the state-dependent model does not improve fit over the fixed-parameter model at conventional information-criterion thresholds, or if the estimated $\kappa\lambda$ is not significantly different from zero, the arousal-dependence component of ACPT should be considered unsupported.

Study 2: Cognitive-load manipulation and weighting-curvature estimation

Hypothesis: experimentally induced cognitive load decreases the individually estimated weighting-curvature parameter γ, consistent with $\gamma(C) = \gamma_0(1 - \kappa\gamma\ C)$.

Design: within-subjects manipulation of load via a graded concurrent working-memory task (e.g., an n-back task at increasing n) performed while eliciting risk preferences, following the general logic of dual-task interference used in the adaptive-decision-maker tradition (Payne et al., 1993).

Elicitation: probability-weighting curvature estimated from certainty equivalents across a range of probabilities for gain-only gambles, separately at each load level, following standard cumulative-prospect-theory elicitation procedures (Tversky & Kahneman, 1992).

Model comparison and falsification criterion: as in Study 1, applied to γ and C; absence of a significant negative relationship between load and estimated γ would count against the load-dependence component of ACPT.

Study 3: Joint manipulation and the symmetric-gamble risk premium

Hypothesis: for a symmetric 50/50 gain/loss gamble, the risk premium increases with arousal and decreases with cognitive load, and the two effects are separable (Proposition 3).

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

Design: a 2×2 (or continuous-by-continuous) within-subjects design crossing the arousal induction of Study 1 with the load manipulation of Study 2, with risk premia elicited for genuinely symmetric fair gambles.

Expected outcome: a significant positive main effect of arousal and a significant negative main effect of load on the elicited risk premium, with no significant interaction, consistent with the model's prediction that the two channels operate independently through distinct parameters.

Falsification criterion: a positive rather than negative effect of load on the risk premium, or a significant interaction inconsistent with additive separability, would indicate that the two state variables are not acting through independent channels as specified, and would require revising the model's functional form.

4.3 Limitations

Several limitations qualify for the present contribution. First, the link functions $\lambda(A)$ and $\gamma(C)$ are specified as linear for parsimony and conservatism, not because the psychological literature establishes linearity; the true functional form, plausibly non-linear given well-documented inverted-U relationships between arousal and performance in the broader psychological literature, is an empirical question the proposed studies are designed to answer, not one this paper resolves. Second, the sensitivity coefficients $\kappa\lambda$ and $\kappa\lambda$ reported in the Results section are illustrative rather than estimated; every quantitative figure in Section 3 should be read as a demonstration of the model's qualitative behavior under a plausible calibration, not as a claim about the true magnitude of state-dependence in any population. Third, the model as specified treats A and C as exogenous and independently manipulable, whereas in naturalistic settings the two are likely correlated which complicates identification outside the controlled conditions of the proposed studies and is a further reason the joint design of Study 3 is necessary rather than optional. Fourth, the model addresses risk, in the sense of known probabilities, and does not extend to ambiguity in the sense of Ellsberg (1961); a natural extension would allow a source-dependent weighting function or a multiple-priors representation to depend on A and C in an analogous way, but this extension is left for future work rather than attempted here. Finally, the present paper reports no primary human-subject data; its claims to descriptive adequacy are conditional on the outcome of the calibration programme proposed in Section 4.2, and the model should accordingly be read as a formal, falsifiable hypothesis rather than an established empirical result.

5. Conclusion

This paper has proposed Affective-Cognitive Prospect Theory, an extension of cumulative prospect theory in which loss aversion increases with momentary affective arousal and probability-weighting curvature decreases with momentary cognitive load, each link grounded in established psychological literature rather than introduced ad hoc. The model nests cumulative prospect theory as a special case, generates testable and in one respect counter-intuitive comparative statics and offers a load-dependent reinterpretation of the size of the Allais paradox. A three-study calibration programme is proposed to estimate the model's two novel sensitivity parameters and to test its separability prediction directly. If supported, the framework would give economics a decision-theoretic vocabulary for state-dependent risk preferences that is currently available in psychology but absent from the standard toolkit of choice under uncertainty; if not supported, the explicit falsification criteria attached to each proposed study identify exactly which component of the model should be revised or abandoned.

References

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'école américaine. Econometrica, 21(4), 503–546. https://doi.org/10.2307/1907921

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. Journal of Economic Perspectives, 27(1), 173–196. https://doi.org/10.1257/jep.27.1.173

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. Quarterly Journal of Economics, 75(4), 643–669. https://doi.org/10.2307/1884324

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. Journal of Behavioral Decision Making, 13(1), 1–17. https://doi.org/10.1002/(SICI)1099-0771(200001/03)13:1<1::AID-BDM333>3.0.CO;2-S

Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. Psychological Bulletin, 127(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). The adaptive decision maker. Cambridge University Press.

Rabin, M. (2000). Risk aversion and expected-utility theory: A calibration theorem. Econometrica, 68(5), 1281–1292. https://doi.org/10.1111/1468-0262.00158

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. European Journal of Operational Research, 177(3), 1333–1352. https://doi.org/10.1016/j.ejor.2005.04.006

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5(4), 297–323. https://doi.org/10.1007/BF00122574

DOI: https://doi.org/10.54216/JIER.040106
Received: January 02, 2026 Revised: February 10, 2026 Accepted: March 21, 2026