

# Proponency as an Applicability Operator: Reconciling Class Probability with Individual Experience

Version 2.0

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## **Abstract**

Probability describes distributions over reference classes rather than outcomes for individuals. Yet probabilistic statements routinely inform individual decision contexts, creating epistemic tension between statistical validity and individual experience. This article introduces proponency as an applicability operator that preserves class probability while regulating its normative role in individual decision-making. The framework specifies when expected-utility maximization remains rationally permissible (positive residual applicability), when it is degraded (approaching epistemic saturation), and when it loses normative force entirely (saturation reached), requiring transition to alternative decision frameworks. Proponency thus contributes to decision theory by establishing boundary conditions on probabilistic optimization: it determines not what to believe, but when belief-based decision rules may legitimately guide action. The framework generalizes insights from recent work on transformative experience, showing that even well-defined class probabilities may be rationally inapplicable to individual choices due to structural displacement.

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## **1. Introduction**

Probability serves as a cornerstone for modern decision-making across medicine, economics, and risk analysis. Yet probability is fundamentally a statement about classes or ensembles, not about the non-repeatable trajectory of a single individual. When we tell a patient they have a “20% chance” of a surgical complication, we make a statement about a class of similar patients, not a property inherent to that person.

This creates a problem not merely for epistemology but for decision theory. Expected-utility maximization—the dominant normative framework for rational choice under uncertainty—presupposes that probabilities can be meaningfully applied to the options an agent faces. But if the agent’s structural position diverges sufficiently from the reference class generating those probabilities, what remains of the normative force of expected-utility reasoning?

This article proposes that the applicability of probabilistic decision theory is itself a variable requiring assessment. By introducing proponency as an operator adjusting the applicability of class probability, we address not only the epistemic gap between population statistics and individual experience, but the decision-theoretic question of when probability-based optimization is rationally permitted, degraded, or forbidden.

The term “proponency” is a deliberate neologism denoting structural displacement from a reference class without implying propensity, probability, or causation. It was selected to remain

phonetically proximate to—yet conceptually distinct from—“propensity,” emphasizing structural position relative to a class rather than any inherent tendency.

## **2. Class Probability and Its Limits**

### **2.1 The Reference Class Problem**

Probability’s validity hinges on reference classes—aggregates of comparable instances yielding stable frequencies or Bayesian posteriors. Frequentists like von Mises (1928) and propensity theorists like Popper (1959) agree: probability pertains to ensembles, not isolated events.

The “reference class problem,” formalized by Reichenbach (1949) and refined by Hájek (2007), exemplifies the difficulty: any individual fits infinitely many classes, each implying different probabilities. Selecting a “correct” class is ultimately arbitrary. Hájek demonstrates this undermines the justification of probabilistic decisions, as rational agents may arrive at incompatible probability assignments without principled resolution. The traditional response—seeking the narrowest reference class with reliable data—eventually produces sample sizes too small for frequency estimation, ultimately reaching  $n=1$  where frequentist probability loses meaning.

### **2.2 Treatment Effect Heterogeneity**

In medicine, this manifests as the “fallacy of the average patient” (Sackett et al. 1996). Modern clinical research increasingly recognizes Heterogeneity of Treatment Effect (HTE)—individuals within well-defined classes respond differently despite sharing class membership.

Even in perfectly defined classes, the “average” outcome often describes no actual member. A treatment with 60% success may work for virtually all members of one subgroup and none of another; the 60% characterizes population distribution but applies to no individual as such. Kent et al. (2018) highlight that individual responses deviate systematically from averages due to biological variability, comorbidities, or unmeasured confounders. Structural displacement is not merely philosophical abstraction but empirical reality with decision-theoretic consequences.

### **2.3 Defenders of Single-Case Probability**

Some philosophers defend single-case probabilities. Propensitists such as Fetzer (1981) and Mellor (1971) argue probabilities can be grounded in physical dispositions inherent to specific setups.

The present framework acknowledges this appeal but does not adopt it. Propensity theories face difficulties: circularity in defining propensities, conflicts with probability axioms, and challenges specifying when setups are “relevantly similar.” More fundamentally, even if single-case propensities exist, the epistemic problem remains: how do we know what propensity applies to this case? And even if we did, the decision-theoretic problem would persist: when is it rational to act on that knowledge? Propensity addresses these dimensions without metaphysical commitments about whether single-case probabilities are ontologically real.

### ***3. Propensity as an Applicability Operator***

#### **3.1 Definition**

Individual propensity is an ordinal descriptor of the degree to which an individual's trajectory is structurally displaced relative to a probabilistic reference class. It is neither a probability, causal factor, nor predictive variable—it is a regulator of epistemic and decision-theoretic confidence.

High propensity indicates applying class probability directly is epistemically hazardous (the statistical “outlier”). Low propensity indicates class probability may be applied with relatively little distortion (the “typical” case). Propensity does not explain why outcomes occur; it constrains how confidently probabilistic expectations—and the decision rules built upon them—may be used.

#### **3.2 Distinction from Propensity**

Propensity theory (Popper 1959) defines singular probabilities inherent in experimental setups, making claims about physical dispositions grounding single-case probabilities. Propensity makes no such claim. Where propensity says “this setup has probability  $p$ ,” propensity says “the class probability  $p$  has limited applicability to this case, and decision rules presupposing that applicability inherit that limitation.”

#### **3.3 Relation to Keynesian Weight**

Propensity parallels Keynes's (1921) “weight of evidence,” where accumulating information modulates confidence in a probability without altering the probability itself. Two probability judgments might share numerical values yet differ in weight—the evidence supporting them.

Propensity operationalizes a related insight: as evidence of structural displacement accumulates, warrant for applying class probability diminishes—and with it, the normative force of decision rules that presuppose such application. Where Keynesian weight concerns the evidential basis of a probability judgment, propensity concerns that judgment's applicability to a particular case and the decision-theoretic consequences of diminished applicability.

#### **3.4 Risk, Uncertainty, and the Limits of Expected Utility**

The framework connects to Knight's (1921) distinction between risk (situations where probabilities can be meaningfully assigned) and uncertainty (situations where they cannot). Propensity marks transitions from measurable risk into structural uncertainty—not uncertainty about the probability, but uncertainty about whether probabilistic decision rules apply at all.

When propensity is high and applicability low, the individual no longer operates under conditions where expected-utility maximization has clear normative standing. The agent has not lost access to probabilities—the class probabilities remain valid—but has lost the epistemic warrant to treat those probabilities as decision-relevant for their particular case.

### ***4. Propensity and Decision Theory: A Boundary Condition on***

## ***Rational Choice***

### **4.1 The Decision-Theoretic Role of Proponency**

Proponency does not compete with probability theory or decision theory. It operates at a prior level, determining which decision framework is applicable under given epistemic conditions.

Standard expected-utility theory instructs agents to choose the action maximizing probability-weighted utility. This presupposes that probabilities can be meaningfully assigned to outcomes for the agent in question. When class probabilities are the only probabilities available—as is typically the case—expected-utility reasoning implicitly assumes the agent is a relevantly typical member of the reference class.

Proponency makes this assumption explicit and assessable. The residual applicability margin  $\varepsilon$  indicates whether the implicit assumption holds:

**$\varepsilon > 0$  (Positive Applicability):** The agent's displacement from the reference class is modest. Expected-utility maximization retains its normative force. The agent may rationally optimize using class probabilities as inputs.

**$\varepsilon \approx 0$  (Approaching Saturation):** Displacement is substantial. Expected-utility calculations remain possible but their normative force is degraded. The agent should widen confidence intervals, consider robustness across probability assignments, and prepare for deviation from expected outcomes.

**$\varepsilon \leq 0$  (Epistemic Saturation):** Displacement equals or exceeds the discriminatory power of the class probability. Expected-utility maximization loses its normative warrant. The agent must transition to decision frameworks designed for conditions of genuine uncertainty.

This is not a modification of probabilities or utilities. It is a boundary condition on when probability-based optimization is rationally permitted.

### **4.2 Alternative Decision Frameworks at Saturation**

When  $\varepsilon \leq 0$ , the framework mandates transition from expected-utility reasoning to alternatives appropriate for structural uncertainty:

**Precautionary Reasoning:** Prioritize avoiding worst-case outcomes over maximizing expected value. Appropriate when potential losses are severe or irreversible and probabilistic guidance is unavailable.

**Minimax / Maximin Strategies:** Choose the option whose worst possible outcome is least bad, without probability weighting. This strategy requires only ordinal comparison of outcomes, not probabilistic expectations.

**Satisficing:** Identify options meeting minimum acceptable thresholds rather than optimizing. When probability-based optimization lacks warrant, “good enough” may be the most defensible target.

**Reversibility and Optionality:** Structure decisions to preserve future options and allow course correction. When probabilistic prediction fails, maintaining flexibility becomes a rational priority.

**Expert Consultation with Explicit Uncertainty:** Seek qualitative guidance from domain experts, with explicit acknowledgment that probabilistic precision is unavailable.

The key insight is that reaching epistemic saturation does not leave the agent without rational recourse. It redirects them toward decision frameworks designed for genuine uncertainty rather than measurable risk.

### 4.3 Propensity and Transformative Experience: A Conceptual Bridge

Recent work in decision theory has identified a structurally similar problem. L.A. Paul (2014) and Richard Pettigrew (2019) have examined “transformative experiences”—choices that fundamentally alter the agent’s preferences, values, or epistemic position in ways that cannot be anticipated from the agent’s current standpoint. Pettigrew’s *Choosing for Changing Selves* develops formal frameworks for rational choice when the agent cannot evaluate post-decision outcomes using pre-decision preferences.

The parallel to propensity is instructive. In transformative experience, the problem is that the agent’s current utility function cannot reliably evaluate outcomes that will be experienced by a transformed self. In propensity, the problem is that class probabilities cannot reliably guide decisions for an agent whose structural position diverges substantially from the reference class.

Both frameworks identify conditions under which standard expected-utility theory loses its normative grip—not because the theory is wrong, but because its applicability conditions are not met. Just as transformative experience challenges expected-utility theory by questioning whether current preferences can evaluate future outcomes, propensity challenges expected-utility theory by questioning whether class probabilities can guide individual decisions.

However, propensity generalizes the problem in an important respect. Transformative experience focuses on cases where the agent’s preferences or identity will change. Propensity applies even when preferences are stable, addressing cases where the agent’s epistemic position relative to statistical evidence is structurally compromised. An agent facing a medical decision may have perfectly stable preferences and clear values, yet still find that class-derived probabilities do not warrant expected-utility reasoning due to their atypical medical history.

The frameworks are complementary rather than competing. Transformative experience identifies one source of expected-utility inapplicability (preference instability across the decision). Propensity identifies another (structural displacement from reference classes). Both contribute to a broader understanding of the boundary conditions on probabilistic decision-making.

## 5. The Principle of Propensity

### 5.1 Statement

The Principle of Propensity states that class probability remains valid at the population level but must be adjusted in its individual application by an operator reflecting persistent individual deviation. This adjustment modifies applicability—and thereby the normative standing of probability-based decision rules—not probability itself.

The principle permits individual use of class probability without reinterpreting it as an individual probability. It specifies when expected-utility maximization is rationally permitted (positive  $\epsilon$ ),

when it is degraded ( $\epsilon$  approaching zero), and when it must yield to alternative decision frameworks ( $\epsilon \leq 0$ ).

## 5.2 Epistemic Saturation as a Decision-Theoretic Threshold

Epistemic saturation is reached when the agent's aggregate adjustment load equals or exceeds the class-level adjustment differential. At this point:

- Class probability provides zero informational value for individual decision-making.
- Expected-utility calculations, while mathematically possible, lack normative warrant.
- The agent has not entered a realm of irrationality but a realm requiring different rational procedures.

This threshold reflects a genuine boundary: when displacement equals or exceeds the class probability's discriminatory power, probabilistic optimization is not merely difficult but normatively inappropriate.

## 5.3 Scope and Limits

The framework preserves class probability as the only genuine probability, introduces an ordinal operator encoding persistent displacement, provides criteria for when expected-utility reasoning retains normative force, and specifies alternative decision frameworks when it does not.

The framework does not predict individual outcomes, generate personalized probabilities, explain deviation causes, replace statistical models, or modify utility functions. It establishes boundary conditions on rational choice under uncertainty.

## 6. Heuristic Formalization

**Important Notice:** The following expression is heuristic and illustrative only. It must not be treated as a computable function, calibrated model, or cardinal measure. All variables are ordinal and context-dependent.

The principle is expressed as:

$$\epsilon = \omega (\Delta\psi - \Sigma)$$

This positions  $\omega$  as a coefficient of resilience. High stability amplifies the net applicability signal; low stability dampens it regardless of individual load.

### Variables:

$\epsilon$  (*Residual Applicability Margin*): How far class probability—and expected-utility reasoning based upon it—remains normatively warranted. Positive values indicate probabilistic optimization is permitted; values near zero indicate degraded warrant; negative values indicate expected-utility reasoning should be suspended.

$\omega$  (*Baseline Applicability Capacity*): Structural capacity to sustain probabilistic reasoning, aggregating psychological stability, situational resilience, and contextual regularity.

$\Delta\psi$  (*Class-Level Adjustment Differential*): Degree to which alternative actions are distinguished at the population level. Captures the discriminatory power of class probability for the decision at hand.

$\Sigma$  (*Aggregate Individual Adjustment Load*): Cumulative factors eroding applicability—repeated deviation, unexplained outcome concentrations, unique exposures.

When  $\Sigma = \Delta\psi$ , the expression yields  $\varepsilon = 0$ —the saturation point where displacement neutralizes discriminatory power. When  $\Sigma > \Delta\psi$ ,  $\varepsilon$  becomes negative, signaling that expected-utility reasoning based on class probability lacks normative warrant.

## 7. Illustrative Example: Decision-Theoretic Inapplicability

Consider an agent choosing between two medical treatments, A and B. Published clinical data indicate:

- Treatment A: 70% success rate in the reference population
- Treatment B: 60% success rate in the reference population

For a typical member of the reference class, expected-utility reasoning clearly favors Treatment A (assuming success and failure have symmetric utilities across treatments).

Now consider Patient X, who has experienced adverse outcomes in four previous medical interventions where population statistics predicted favorable results, has a rare autoimmune condition unrepresented in either treatment’s clinical trials, and has been explicitly told by specialists that “standard statistics may not apply” to their case.

Patient X’s  $\Sigma$  score is high (8 on the UPA-10 scale). Their residual applicability margin  $\varepsilon$  is at or below zero.

**The decision-theoretic consequence:** The ordering of treatments by expected utility—A preferred to B because  $0.70 > 0.60$ —loses its normative force for Patient X. The class probabilities remain true statements about the reference populations, but they do not warrant expected-utility reasoning for this patient.

Patient X is not irrational to decline Treatment A despite its higher class success rate. Nor are they irrational to choose Treatment B, or to seek a third option, or to delay decision pending further information. What would be irrational is to treat the 70% vs. 60% comparison as providing the same decision-theoretic guidance it would provide for a typical class member.

For Patient X, appropriate decision frameworks might include:

- **Minimax:** Which treatment has the less severe worst-case outcome?
- **Reversibility:** Which treatment preserves more future options if it fails?
- **Qualitative expert judgment:** What do specialists familiar with their specific condition recommend, independent of population statistics?

The example illustrates that proponency does not tell Patient X what to choose. It tells them that expected-utility comparison based on class probabilities is not the right decision procedure for their situation.

## 8. Practical Operationalization

### 8.1 The Universal Proponency Assessment

The Aggregate Individual Adjustment Load ( $\Sigma$ ) requires operationalization. The following 10-

item binary instrument was designed for domain neutrality and structural focus. Each “Yes” contributes 1 unit, yielding  $\Sigma \in [0, 10]$ .

1. *Recurrent Statistical Defiance*: In past situations where most people experienced Outcome A, have you consistently experienced Outcome B?
2. *Contextual Uniqueness*: Are there stable features of your environment or constitution likely excluded from the population data generating the prediction?
3. *Accumulated Exposure*: Have you been subjected to the process so many times that your exposure history distinguishes you from typical cases?
4. *Signal Asymmetry*: Do your personal baseline measurements consistently fall at extreme edges of the reference distribution?
5. *Historical Clustering*: Have “rare” events occurred with frequency exceeding chance expectations?
6. *Information Gap*: Does the class-based model rely on assumptions you know to be false in your case?
7. *Systemic Interconnectivity*: Does your situation involve multiple overlapping systems interacting in ways the single-domain model fails to capture?
8. *Persistent Residue*: Are you dealing with after-effects of a previous outlier event influencing your trajectory?
9. *Predictive Failure*: Have previous models regarding your situation failed significantly more often than succeeded?
10. *Intuitive Structural Misalignment*: Do you possess a persistent, evidence-supported sense that the typical path is structurally unavailable?

## 8.2 Interpretation and Decision-Theoretic Implications

**$\Sigma$  Score 0–2 (High Congruence)**: Expected-utility maximization fully warranted.

**$\Sigma$  Score 3–5 (Moderate Displacement)**: Expected-utility reasoning permitted but with widened uncertainty.

**$\Sigma$  Score 6–7 (Substantial Displacement)**: Expected-utility reasoning degraded; supplement with robustness checks.

**$\Sigma$  Score 8–10 (Structural Outlier)**: Expected-utility reasoning unwarranted; transition to alternative frameworks.

## 9. Distinguishing Propensity from the Gambler’s Fallacy

Propensity must be distinguished from the Gambler’s Fallacy—the mistaken belief that random sequences must “self-correct.”

The Gambler’s Fallacy assumes the underlying process is random and independent, then erroneously infers past outcomes influence future ones. Propensity makes no such assumption. Rather, propensity recognizes that the system may not be relevantly similar for this individual—that structural factors exist such that class probability, while valid for the class, does



not warrant the same decision procedures it would warrant for a typical member.

The Gambler's Fallacy is a cognitive error within probabilistic reasoning. Proponency is recognition that probabilistic decision-making itself may have limited normative scope for a given agent.

## **10. Objections and Responses**

### **10.1 "This is Bayesian Updating"**

Bayesian updating produces new probabilities—posteriors incorporating prior beliefs and evidence. Proponency does not produce new probabilities. It assesses whether existing class probabilities warrant expected-utility reasoning for a particular agent. The output is not a revised probability but a judgment about the normative standing of probability-based decision rules.

### **10.2 "The Framework is Unfalsifiable"**

This objection misconstrues scope. Proponency is not an empirical hypothesis but a normative framework establishing boundary conditions on rational choice. Like decision theory itself, it cannot be falsified in the strict sense but can be evaluated by coherence, practical utility, and alignment with considered judgments about when probabilistic optimization is appropriate.

### **10.3 "Why Not Narrower Reference Classes?"**

This traditional response has merit where feasible. However, narrowing eventually produces sample sizes too small for reliable estimation. Additionally, relevant individual factors may not correspond to established subgroups with available data.

The approaches are complementary: use narrow reference classes when available; use proponency assessment when subclassification is unavailable or insufficient to restore expected-utility warrant.

## **11. Conclusion**

The Principle of Proponency contributes to decision theory by establishing explicit boundary conditions on probabilistic optimization. It specifies when expected-utility maximization is rationally permitted (positive residual applicability), when its normative force is degraded (approaching saturation), and when it must yield to alternative decision frameworks designed for genuine uncertainty (saturation reached).

The framework does not modify probabilities or utilities. It does not predict individual outcomes or generate personalized probability assignments. What it provides is a principled answer to a question decision theory has largely left implicit: under what conditions does an agent have normative warrant to apply expected-utility reasoning based on class probabilities?

By making the applicability conditions of probabilistic decision-making explicit and assessable, proponency extends recent insights from work on transformative experience to a broader class of cases. Even when preferences are stable and class probabilities well-defined, structural displacement may undermine the normative force of expected-utility reasoning. Recognizing this

boundary is not a retreat from rationality but an expansion of it—an acknowledgment that rational choice under uncertainty requires not only decision rules but also criteria for when those rules apply.

In a world saturated with probabilistic claims, the Principle of Proponency offers clarity about where probability-based optimization legitimately governs choice—and where individual judgment, guided by alternative decision frameworks, must responsibly take its place.

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## **Acknowledgements**

This article benefited from correspondence with Professor Alan Hájek, whose remarks emphasized the importance of connecting this framework explicitly to decision theory—particularly in light of recent work on transformative experience. The decision-theoretic interpretation of proponency developed in Section 4 was substantially clarified in response to his guidance.

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