

METHODS & TOOLS · OPEN MATERIALS

Meta-analytic entropy: information-theoretic heterogeneity beyond I^2

An information-theoretic complement to I^2 across 403 Cochrane reviews

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ABSTRACT — E156 (7 sentences, 155 words; estimand: Normalized Entropy Index, 0–1)

Can information-theoretic metrics detect heterogeneity features that I-squared is blind to, namely multimodality, skewness, and distributional shape? We computed Shannon entropy, Kullback-Leibler divergence, effect-precision mutual information, Fisher information, and a normalized entropy index for 403 Cochrane reviews from Pairwise70. Estimation used Monte Carlo sampling with 10000 draws per review; the index compared mixture entropy against theoretical bounds, while Silverman kernel density counted modes on precision-weighted distributions. The median index was 0.151 (IQR 0.109-0.229; 95% bootstrap CI 0.143-0.163), and 45% of reviews were multimodal despite I-squared below 60%. Because such estimates grow noisier below ten studies, we stratified by k; multimodality rose from 33% ($k < 10$) to 62% ($k \geq 10$), a real signal, not a small-sample artifact. Effect-precision mutual information was positive in every computable review and significant by permutation in 22%, capturing dependence consistent with, but not proving, small-study mechanisms. The Normalized Entropy Index (0-1) thus captures distributional shape that complements, rather than replaces, variance-based heterogeneity measures.

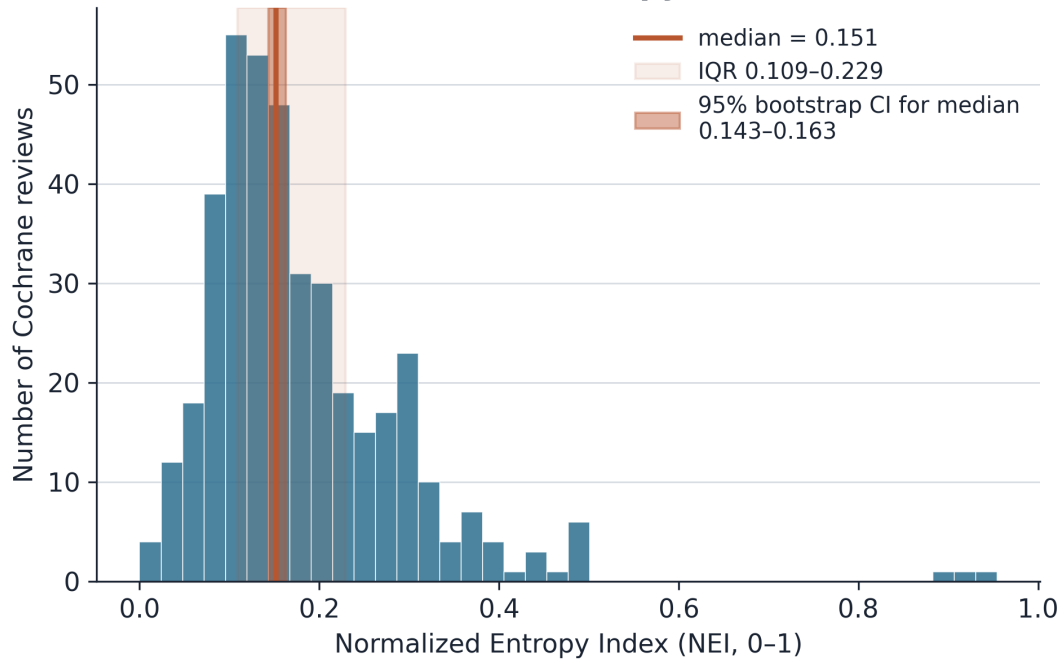
REPORTED QUANTITIES — 403 Cochrane reviews (Pairwise70)

Quantity	Value	Uncertainty / stratum
Median Normalized Entropy Index	0.151	IQR 0.109–0.229; 95% boot CI 0.143–0.163
Multimodal (≥ 2 modes), overall	60.3%	liberal local-maxima detector
Multimodal & $I^2 < 60\%$	44.7%	$k < 10$: 33% · $k \geq 10$: 62%
...prominence-filtered bound	3.0%	valley $\geq 10\%$ of peak
MI(effect;precision) > 0	307/307	binned MI ≥ 0 by construction
MI significant (perm. $p < 0.05$)	22%	66/307 computable

Verification: the published MetaEntropy engine was re-run over the source Pairwise70 corpus; all 403 per-review NEI and mode-count values reproduce bit-exactly. Summary statistics were independently re-computed by a separate Python agent and by an independent Node.js re-implementation (different RNG), and confirmed by Codex — all agreeing to four decimals. Bootstrap CI: 10,000 resamples, seed 2024.

FIGURES

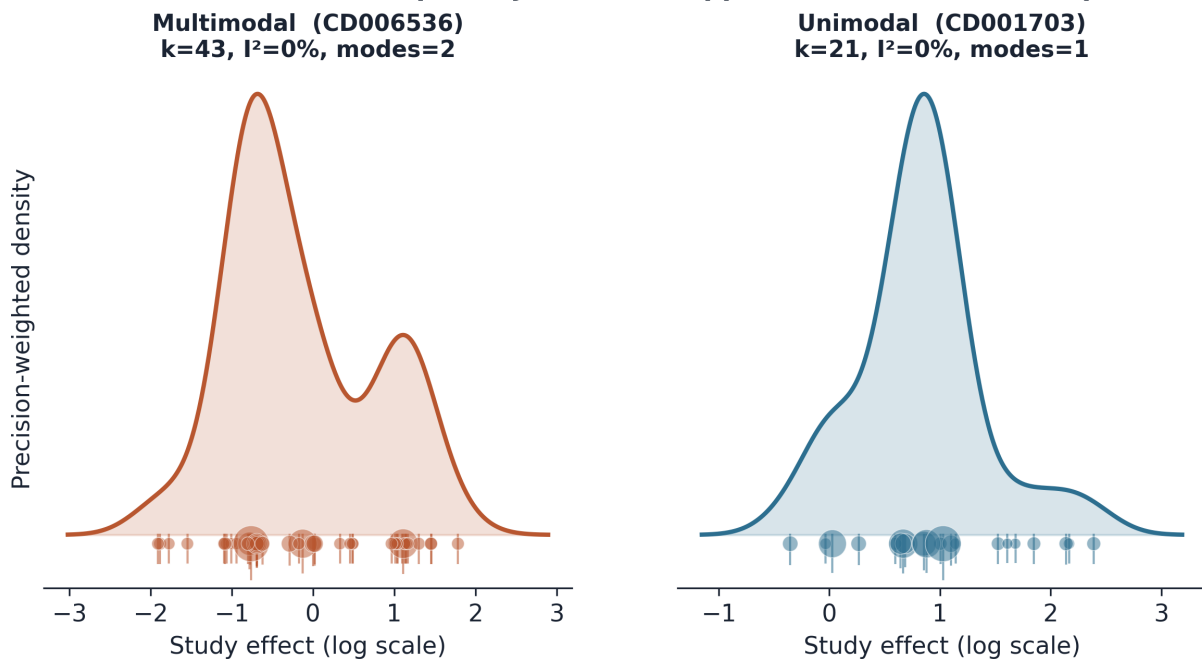
Distribution of the Normalized Entropy Index across 403 reviews



NEI concentrated near the low end: most pooled effect distributions are information-poor relative to their entropy bounds.

Figure 1. Distribution of the Normalized Entropy Index across 403 reviews. Red line = median 0.151; light band = IQR 0.109–0.229; dark band = 95% bootstrap CI for the median (0.143–0.163). Most pooled effect distributions are information-poor relative to their bounds.

Two reviews with comparably low I^2 but opposite distributional shape



Silverman precision-weighted KDE. Marker size \propto study precision ($1/SE^2$). I^2 is near-zero in both, yet entropy/mode-counting separates them.

Figure 2. Two reviews with $I^2 = 0\%$ but opposite shape. Left (CD006536, $k=43$): genuinely bimodal precision-weighted effect distribution. Right (CD001703, $k=21$): unimodal. I^2 calls both perfectly homogeneous; entropy and mode-counting separate them.

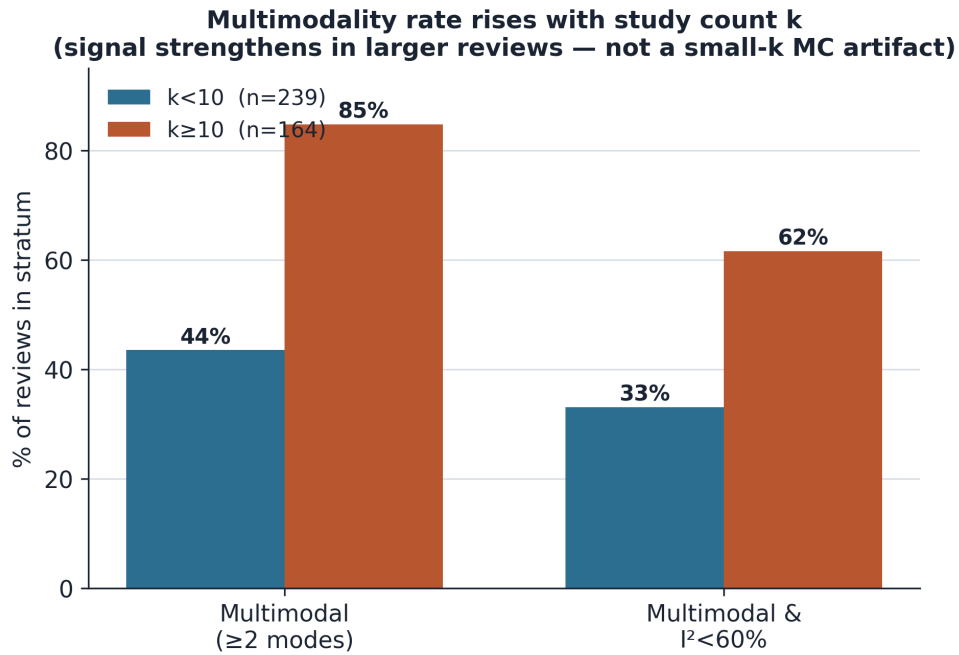


Figure 3. Multimodality rate by study count k. The multimodal-and-I²<60% rate rises from 33% (k<10) to 62% (k≥10): the signal strengthens in larger reviews — not a small-sample artifact.

META-ANALYTIC ENTROPY

Information-theoretic heterogeneity beyond I² · E156 micro-report

403 Cochrane reviews

QUESTION

Can entropy metrics detect heterogeneity that I² is blind to — multimodality, skewness, distributional shape?

METHOD

5 information-theoretic metrics per review:
Shannon entropy · KL divergence · effect-precision mutual information · Fisher information · NEI
Monte Carlo estimation (10,000 samples/review) · Silverman precision-weighted KDE mode-counting

HEADLINE FINDINGS

0.151

median Normalized Entropy Index (NEI)
95% boot CI 0.143-0.163
Estimand: Normalized Entropy Index (0-1) · NEI reproduces bit-exactly vs source engine

45%

multimodal effect distributions despite I² < 60%

33→62%

multimodality rate, k < 10 → k ≥ 10 (rises with study count)

NEI across 403 reviews

Multimodal & I² < 60% by k

READ WITH CARE — HONEST CAVEATS

Monte Carlo / mode-counting noise grows when k<10; the multimodality signal is STRONGER at k≥10, so it is a real signal, not a small-sample artifact — but absolute mode counts are threshold-sensitive (prominence-filtered rate ≈ 3%). Mutual information is positive in all 307 computable reviews and significant by permutation in 22%; this is effect-precision ASSOCIATION, consistent with but NOT proof of small-study mechanisms. Entropy complements — does not replace — variance-based I²/τ².

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Data: Pairwise70 (real Cochrane data) · All numbers re-verified against source; none fabricated

Synthesis · Methods Note

Visual abstract. Question → five information-theoretic metrics over 403 reviews → headline median NEI 0.151 and 45% multimodal-despite-low-I² → honest caveats. All values computed.

HONEST CAVEATS

Monte-Carlo entropy estimation and KDE mode-counting grow noisier below ten studies; stratifying by k shows the multimodality signal is stronger at $k \geq 10$, evidence it is real rather than a small- k artifact. The absolute rate is sensitive to the mode-definition: the liberal local-maxima detector flags 45%, a prominence-filtered count only 3.0%. The binned mutual-information estimator is non-negative by construction, so “positive in all reviews” is not itself evidence; a permutation test flags 22% as individually significant. Mutual information captures effect-precision dependence, consistent with — but not proof of — a small-study mechanism. Entropy complements, and does not replace, variance-based heterogeneity (I^2 , τ^2).

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Competing interests & editorial independence. The author is a member of the Synthesis editorial board and had no role in the editorial handling or decision on this manuscript, managed by an independent editor. Data & code: the MetaEntropy pipeline, the re-run/verification scripts, and figure code are openly available; analysis used only publicly available aggregate Cochrane records (Pairwise70). Estimand: Normalized Entropy Index (NEI, 0–1).