Relevant and Reliable Information

The most sophisticated analysis becomes worthless when built on quicksand. In strategic decisions, teams often drown in data while missing the handful of facts that actually matter. **Relevant and Reliable Information**—the third link in **Decision Quality (DQ)**—isn't about gathering *more* information; it's about knowing **what to trust** and **when to stop**. Once you've framed the right question (step 1) and generated alternatives (step 2), this step determines whether your analysis produces **insight** or **illusion**.[6]

The theory in brief (why information quality determines strategy outcomes)

Strategic choices unfold under uncertainty. Leaders naturally try to reduce that uncertainty with more analysis—but additional data only improves a decision when it would change what you choose or meaningfully shift the odds. **Expected Value of Information (EVI)** formalizes this intuition: if learning something wouldn't alter the choice, or the benefit is smaller than the cost and delay of acquiring it, move forward.[1,2]

Even with the right focus, teams systematically misuse information. They over-rely on the **inside view**—detailed narratives about *this* project, *our* market, *our* capabilities—while ignoring **base rates**. Decades of research show this pattern produces predictable errors: optimism bias, planning fallacy, and base-rate neglect.[3,4] The remedy is the **outside view** via **reference class forecasting**: find comparable efforts, examine the outcome distribution, and adjust from that baseline. Well-implemented reference classes have been associated with markedly better cost and schedule realism in large programs.[7]

Information quality depends as much on **process** as on **sources**. **Procedural rationality**—clear, information-rich methods—correlates with more effective strategic decisions.[5] In practice this means distinguishing **facts** from **assumptions** from **opinions**, triangulating across methods and sources, and applying basic **credibility tests** (e.g., peer-reviewed vs. personal blog; primary data vs. anecdote; independent corroboration). When these disciplines combine, you get information that is both **relevant** (decision-critical, timely) and **reliable** (accurate, traceable)—exactly what DQ demands.[6]

From theory to practice: making information relevant *and* reliable

These seven practices operationalize decades of research on judgment under uncertainty, turning academic insight into executive discipline.

A. Start with decision-critical uncertainties

Why it works.	**What good looks like.**
Sensitivity analysis shows most strategic choices pivot on a **small set** of variables while remaining insensitive to dozens of others; in decision trees and influence diagrams only variables that can **flip the preferred alternative** or materially change expected value warrant deep investigation.[1,2,9] Focusing on those few uncertainties is a core expression of **procedural rationality**, which correlates with higher strategic decision effectiveness.[5]	An **Uncertainty Map** listing **3–5** variables that swing the decision, each with rough sensitivity and the **minimum evidence** needed. Everything else explicitly out of scope. If it won't change the choice, it's not on the map.

B. Use Expected Value of Information (know when to stop)

Why it works.	**What good looks like.**
Information value theory Expected Value of Perfect Information (EVPI) / Expected Value of Sample Information (EVSI) formalizes when learning is worth it: additional data has value only if it **changes the choice or the odds** net of cost and delay.[1,2] Executives often grasp the idea but skip even rough calculations, leading to both analysis paralysis (negative VOI) and missed high-VOI opportunities.[1]	A **VOI calculation** per major uncertainty showing **value of learning vs. cost/delay** and a clear **STOP/CONTINUE** call. When VOI < cost (including **cost of delay**), move forward; if VOI is high but time-constrained, convert to a **small, fast test** (see G).

C. Anchor forecasts in base rates (the outside view)

Why it works.	**What good looks like.**
Base-rate neglect is a robust error: people overweight case specifics and ignore class statistics.[3] **Reference class forecasting** counters this by anchoring estimates in the **observed distribution** of comparable efforts; in large programs this improves cost and schedule realism materially.[4,7]	A **Base-Rate Box**: reference class (**n ≥ 10**), median and **10th/90th** percentile outcomes, and the **delta** to the inside-view estimate. The final forecast explicitly reconciles any material deviation from the base rate with **testable reasons**.

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D. Apply source credibility and triangulation

Why it works.	**What good looks like.**
Combining **independent** estimates reduces error proportional to their independence and individual accuracy (the “wisdom of crowds” effect); structured triangulation across methods raises validity.[9,11,12] Classic decision-trap research shows single-source reliance creates blind spots; **credibility tests** (peer-reviewed vs. blog; primary data vs. anecdote; independent corroboration) reduce systematic error.[8,12,13]	A one-page **Source Table** for decision-critical claims: source type, provenance/date, known biases, **corroboration status**. Each input labeled **Fact / Supported assumption / Opinion**. No single-source dependencies on critical elements.

E. Balance internal and external evidence

Why it works.	**What good looks like.**
Organizations tend toward **local search** (over-relying on familiar, internal information). Integrating **internal specificity** with **external benchmarks** (market/competitor/technology) improves judgment quality and guards against echo chambers; comprehensive, information-rich processes are linked to more effective strategic decisions.[5,6]	A **360° Evidence Panel** placing internal trends beside external indicators with a one-line **convergence/divergence** read-out. When signals conflict, include one **testable hypothesis** for reconciliation and the check that will resolve it.

F. Make uncertainty explicit (calibration beats false precision)

Why it works.	**What good looks like.**
Overconfidence is pervasive; most forecasters are under-calibrated at high confidence levels. Expressing **ranges/probabilities** with short confidence notes forces recognition of unknowns and enables **Bayesian-style updating** as evidence arrives; elite forecasters differentiate themselves primarily by **calibration**, not clairvoyance.[9,11]	All critical estimates as **P10–P50–P90** ranges (or explicit probabilities) plus a two-bullet **confidence note**: drivers of uncertainty and the **next update**. Point estimates are banned for decision-critical quantities; top forecasts get a **quarterly calibration review**.

G. Learn fast: turn assumptions into facts

Why it works.	**What good looks like.**
Discovery-driven planning treats learning as a staged investment: identify "killer assumptions," run cheap, fast tests, and adjust commitment based on evidence—real-options logic for strategy.[10] This converts high-VOI assumptions into observed data quickly.	A **Learn-then-Decide** plan: **1–2 rapid tests** (pilot, pre-order, external panel) with **kill/surge triggers** ("If paid conversion ≥ 5% on 200 invites → proceed; if < 3% → pivot/stop"). Every critical assumption either has base-rate support **or** a scheduled test with **date-stamped** rules.

Practical limitations (and how to work with them)

- **Information that won't move the choice.** Teams chase "interesting" facts rather than decision-critical ones. Start with an **Uncertainty Map** (the 3–5 variables that swing value). Tie every data request to a mapped uncertainty and include a one-line **VOI note**; if VOI < cost of delay, move.[1,2,9]
- **Confirmation shopping and single-source linchpins.** Preference-consistent search produces fragile conclusions. Use a one-page **Source Table** for decision-critical claims (type, provenance/date, biases, **corroboration status**). Demand independent **triangulation** (≥2 sources) or a dated plan to obtain it, and schedule a 30-minute **adversarial evidence review** before down-select.[8,12,13]
- **False precision and overconfidence.** Point estimates invite misplaced certainty. Express all decision-critical quantities as **P10–P50–P90** (or probabilities) with a two-bullet **confidence note** (drivers of uncertainty; next update). Run **quarterly calibration** on the top forecasts (e.g., Brier scores).[9,11]
- **Sparse or noisy data.** Strategic questions rarely come with clean datasets. Use **structured expert judgment** (document rationales; avoid groupthink), anchor with **adjacent base rates**, prefer **replicable** findings over one-offs, and convert high-value assumptions into **rapid tests** where possible.[2,3,10]
- **Information politics.** Incentives shape what is surfaced and how it's framed. Separate **evidence generation** from **decision rights** (name an **Evidence Lead** distinct from the "D"), standardize artifacts (Uncertainty Map, Base-Rate Box, Source Table, VOI notes), and run a brief **red-team** challenge of the evidence pack.[5,6,8,12]
- **Divergent internal vs. external signals.** Internal metrics offer specificity; external indicators provide context—often on different clocks. When they conflict, state the **most plausible reconciliation** (e.g., mix shift, sampling bias) and the **check** (experiment, audit, third-party data) that will resolve it by a date.[5,6]

Generative AI as scaffold (not substitute)

Where AI helps. Draft **reference classes** and external benchmarks; summarize qualitative corpora (VOC, interviews) into themes; assemble **issue trees** and **uncertainty maps**; highlight **conflicts** among sources; propose **ranges** using comparable cases. This accelerates relevance (focus) and reliability (coverage).[3,4,7]

Where AI must not replace you. Don't outsource **values**, **risk posture**, or **confidence calls**. Require **source-tagging** (asserted vs. cited) and a short **confidence note** with any model output; keep sensitive data within approved environments.[6,12]

A quick AI-assisted pass.

1. List the **3–5 decision-critical uncertainties** and the **minimum evidence** that would move the choice.
2. Generate **reference classes** and base rates (medians + spreads) from credible sources.
3. Summarize **convergent themes** across internal dashboards, customer comments, and analyst reports; flag inconsistencies.
4. Draft **ranges** and a **VOI note** for each uncertainty; recommend where to stop or run a small test.[1-4]

Bottom Line

Information doesn't have to be perfect; it has to be **fit for the decision**. Prioritize decision-critical uncertainties, use VOI to stop, anchor on base rates, and enforce credibility and triangulation. Do that, and you'll meet the DQ standard for **Relevant & Reliable Information**—without boiling the ocean. The payoff is faster, clearer choices—and fewer surprises after you commit.[1-7]

References

1. Howard, R. A. (1966). Information value theory. IEEE Transactions on Systems Science and Cybernetics, 2(1), 22–26.
2. Morgan, M. G., & Henrion, M. (1990). Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press.
3. Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. Psychological Review, 80(4), 237–251.
4. Kahneman, D., & Lovallo, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. Management Science, 39(1), 17–31.
5. Dean, J. W., & Sharfman, M. P. (1996). Does decision process matter? A study of strategic decision-making effectiveness. Academy of Management Journal, 39(2), 368–392.
6. Spetzler, C., Winter, H., & Meyer, J. (2016). Decision Quality: Value Creation from Better Business Decisions. Wiley.
7. Flyvbjerg, B. (2006). From Nobel Prize to project management: Getting risks right. Project Management Journal, 37(3), 5–15.
8. Hammond, J. S., Keeney, R. L., & Raiffa, H. (1998). The hidden traps in decision making. Harvard Business Review, 76(5), 47–58.
9. Von Winterfeldt, D., & Edwards, W. (1986). Decision Analysis and Behavioral Research. Cambridge University Press.
10. McGrath, R. G., & MacMillan, I. (1995). Discovery-driven planning. Harvard Business Review, 73(4), 44–54.
11. Tetlock, P. E., & Gardner, D. (2015). Superforecasting: The Art and Science of Prediction. Crown.
12. Russo, J. E., & Schoemaker, P. J. H. (1989). Decision Traps: The Ten Barriers to Brilliant Decision-Making and How to Overcome Them. Fireside.
13. Heath, C., & Heath, D. (2013). Decisive: How to Make Better Choices in Life and Work. Random House.

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Kerr Manson
(847) 602-4275
kerr.manson@breakout-growth.com
www.breakout-growth.com