

## Transparency in Data Driven Decisions

Abi's temptation is very realistic, because you can "stay honest" in a narrow sense, meaning no data are changed, while still steering the narrative by choosing outcomes, subgroups, models, or visualisations that spotlight only what flatters Whizzz. That is not neutral analysis, it is selective emphasis, and it quietly swaps evidence for advocacy. Gelman and Loken describe how many defensible analysis paths exist in real projects, if you only report the path that looks best after you have seen the data, you create a misleading impression of certainty even without fabricating anything.

This matters because data driven decisions rely on an assumed baseline of objectivity. If Abi filters results through his own goals, or the sponsor's goals, he undermines that baseline and increases the risk of false conclusions. Ioannidis argues that bias often comes from analysis and reporting choices, with selective reporting being a common mechanism, and that such practices can make published conclusions less reliable.

Professionally, Abi should treat the harmful signal as central, not inconvenient. A defensible approach is to pre specify and present a primary analysis that directly tests the nutrition claim, report uncertainty and limitations clearly, then place any additional favourable analyses in an explicitly exploratory section, with a plain warning about multiple comparisons and interpretability. This aligns with the ASA's ethical guidance on transparency, integrity in presenting results, and accountability to those who rely on statistical work, not just the paying client.

If Abi expects the manufacturer to publicise only positives, he still has agency. He can insist on an executive summary that foregrounds safety relevant findings, document analytic decisions and caveats in writing, and refuse to sign off on communications that he believes are misleading. The legal and social impacts are also non trivial, selective reporting that downplays harm can contribute to consumer deception, regulatory exposure, and reputational damage, and the ACM principle to avoid harm and be honest supports taking action when foreseeable misuse is likely.

## References

American Statistical Association (2022) *Ethical Guidelines for Statistical Practice*. Available at: <https://www.amstat.org/your-career/ethical-guidelines-for-statistical-practice> (Accessed: 16 December 2025).

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Gelman, A. and Loken, E. (2013) *The garden of forking paths: Why multiple comparisons can be a problem, even when there is no “fishing expedition” or “p hacking” and the research hypothesis was posited ahead of time*. Available at: [https://sites.stat.columbia.edu/gelman/research/unpublished/p\\_hacking.pdf](https://sites.stat.columbia.edu/gelman/research/unpublished/p_hacking.pdf) (Accessed: 16 December 2025).

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