Measuring Reliance Without Judgment

AI adoption is rising fast. The harder question is whether people are preserving judgment, skill, and accountability while using it.

The research problem

Counting AI use is easy. Understanding AI reliance is harder.

The simplest way to measure AI adoption is to count usage: logins, prompts, generated documents, or minutes saved. Those numbers matter, but they can mislead.

A person who blindly accepts an AI-written recommendation and a person who challenges, rewrites, and verifies that recommendation may look identical in a dashboard.

This is why less AI is the wrong goal. The better goal is appropriate reliance: using AI when it improves the work, resisting it when it weakens reasoning, and knowing the difference.

What recent research suggests

Reliance is not the same as trust

Human-AI decision-making research has often measured trust, but recent work argues that stated trust does not reliably tell us whether people rely on AI appropriately.

A better lens is behavioral. Did the person rely on AI when it was correct? Did they push back when it was wrong? Did they adjust when uncertainty changed?

That shift matters because AI reliance is not a personality trait. It changes with the task, expertise, interface design, and social pressure around speed.

A useful finding

Presentation changes reliance more than many people expect

The 2025 REL-A.I. paper takes an interaction-centered view of reliance. Instead of only asking whether a model is calibrated, it asks whether people rely on what the model says.

The paper found that interaction context matters, including knowledge domain and perceived model competence. In one reported example, users relied more on LLMs for calculation questions.

In plain English: people do not only respond to whether AI is right. They respond to how right it sounds.

Why judgment-free measurement matters

Shame produces hiding. Good measurement produces learning.

If organizations frame AI reliance as a character flaw, employees will hide their usage. The better approach is non-punitive measurement.

The question should not be who is using too much AI. It should be where AI is helping, where it creates hidden risk, and where people need better training or workflow design.

Reliance is not always bad. Under-reliance can also be costly. The goal is calibration, not abstinence.

The conclusion

The point is not less AI. It is better human-AI calibration.

AI can make people meaningfully better at work. AI can also make weak reasoning look finished.

The organizations that handle this well will distinguish speed from understanding, acceptance from judgment, and adoption from capability.

That is judgment-free reliance measurement: not surveillance, not moral scoring, not productivity theater. Just a clearer view of how human judgment and machine assistance are changing each other over time.

References

1. Gallup, Rising AI Adoption Spurs Workforce Changes, 2026. https://www.gallup.com/workplace/704225/rising-adoption-spurs-workforce-changes.aspx
2. Gallup, Global Indicator: Artificial Intelligence, 2026. https://www.gallup.com/699797/indicator-artificial-intelligence.aspx
3. Pew Research Center, What the data says about Americans views of artificial intelligence, 2026. https://www.pewresearch.org/short-reads/2026/03/12/key-findings-about-how-americans-view-artificial-intelligenc
4. McKinsey & Company, The State of AI: Global Survey, 2025. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai
5. Raees and Papangelis, From Trust to Appropriate Reliance, 2026 preprint. https://arxiv.org/abs/2604.23896
6. Zhou et al., REL-A.I.: An Interaction-Centered Approach To Measuring Human-LM Reliance, NAACL 2025. https://aclanthology.org/2025.naacl-long.556/
7. Passi et al., Overreliance on AI: Literature Review, Microsoft Research, 2022. https://www.microsoft.com/en-us/research/publication/overreliance-on-ai-literature-review/