

The State of AI in Qualitative and Mixed Methods Research

Key findings on how researchers are adopting, trusting, and governing AI in their qualitative and mixed methods work



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Introduction

Qualitative research has always depended on human judgment—the ability to interpret meaning, weigh context, and see patterns across a body of evidence. In 2026, that judgment is increasingly being paired with AI, but not replaced by it. What researchers are working out, project by project, is not simply where AI can accelerate the work, but something more fundamental: where epistemic authority sits when a machine's output enters the analysis, and how a researcher keeps hold of it.

The question isn't theoretical—it shows up directly in the data. In our 2026 survey of 115 researchers across academic and commercial settings, **57% of researchers already use AI in some form, yet confidence has not kept pace with adoption.** Across all respondents, 87% are concerned about accuracy and hallucination risk, 86% about research integrity, and 85% about data privacy—concerns that intensify, rather than ease, at the analytical core of the work. Trust is highest where AI's output is easiest to verify, and lowest wherever a task requires interpretation.

Look closely at what researchers are actually doing in that gap, and a picture emerges. They verify AI's output against source material. They translate its suggestions into their own analytical language before adopting them. They bound its role—deciding what AI may touch and what remains theirs alone. And they pressure-test its conclusions against their own independent reading of the data. These are not workarounds or reluctant extra labor.

They are the practices through which researchers assert and maintain epistemic authority over their analysis—the same interpretive discipline qualitative research has always demanded, now applied to output no researcher authored.

The problem is that most AI tools give these practices nowhere to live. When verification, translation, and pressure-testing happen outside the software—inside documents, parallel analyses, and ad hoc disclosure decisions—the researcher's judgment is real but invisible, and the rigor it produces leaves no trace.

AI in research should be built around these practices, not despite them: transparent about how it reached a conclusion, traceable back to source material, and never final until a human confirms it. Designed that way, AI doesn't compete with the researcher's authority—it makes the exercise of that authority visible, auditable, and defensible.

In this report, learn where AI has earned researchers' trust, where it hasn't, and why adoption and confidence haven't moved together. You'll also see what these findings mean for the technology this field needs, and the standard we hold our own work to at Lumivero. Whether you're a researcher deciding how far to trust AI in your own work or the one shaping the policy that governs it for others, this report will give you insight to guide your next step.

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Executive summary

The “State of AI in Qualitative and Mixed Methods Research” captures the voices of doctoral researchers, academic faculty, students, and practitioners across research, teaching, and industry settings, spanning experience levels from early-career to over 20 years in the field, to uncover how researchers are adopting, trusting, and governing AI in their qualitative and mixed methods work.

The findings paint a clear picture of both momentum and hesitation. 57% of researchers already use AI in some form, yet the survey responses reveal a fundamental tension: while use is widespread, trust isn't.

Key insights:

- **Adoption is already mainstream among researchers.**
57% of researchers use AI regularly (21%) or occasionally (36%); another 19% have tried AI tools but don't use them consistently.
- **Accuracy, integrity, and privacy are the field's defining concerns.**
87% are concerned or very concerned about accuracy and hallucination risk, 86% about research integrity, and 85% about data privacy—the three highest-ranked concerns in the survey.
- **Trust is highest where AI is easiest to verify, and lowest at the analytical core of the work.**
Researchers report their highest trust in AI for summarizing coded material (34%) and transcription (33%), and their lowest trust for supporting interpretation or sense-making (20%).
- **Distrust of outputs is the biggest barrier to broader use.**
57% cite distrust of AI outputs as their top barrier—ahead of privacy and data security concerns (51%), cost, or lack of training.
- **Researchers are supplying the verification AI doesn't provide.**
61% manually review AI output against source data, and 59% cross-check it against their own independent analysis.
- **The field wants AI to stay in a supporting role.**
48% believe AI should generate suggestions that a researcher reviews and decides on, rather than act independently—rising to 71% among current AI users.

Each finding in this report points in the same direction: researchers don't need to be convinced AI belongs in their work. They need AI that was built to meet the standard they hold their work to.

Where adoption concentrates

Adoption is already widespread, though far from uniform. 57% of researchers already use AI in some form—21% regularly, 36% occasionally—and another 19% have tried it without ever quite making it a habit.

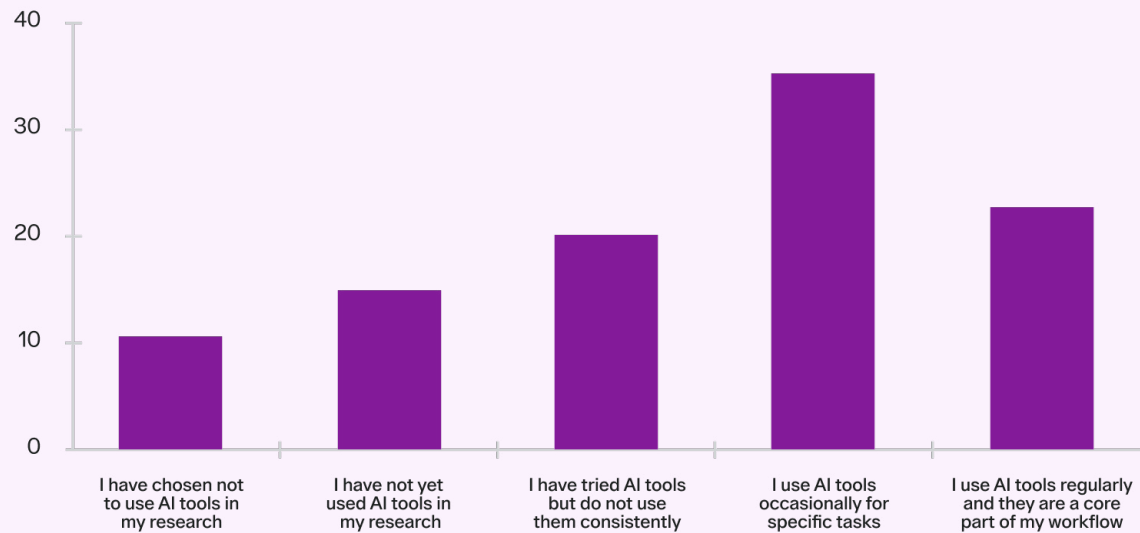
Adoption climbs steadily with experience rather than concentrating among the newest researchers. Looking at regular use as a share of each experience bracket, researchers with 11–20 years in the field have the highest rate of regular use (33%), followed by those with more than 20 years (30%) and those with 6–10 years (25%). The least experienced researchers, those under two years in, are the most likely to sit out entirely showing up disproportionately both among those who haven't gotten around to AI yet and those who've deliberately chosen not to.

Sector shapes the picture just as much as experience does—healthcare trails every other field, with the lowest overall adoption in the sample. Role matters too, and here the pattern flips: doctoral researchers make up the largest group in the survey overall, but among researchers who use AI regularly—faculty and postdoctoral researchers—take the lead instead, at 50% versus 33% for doctoral researchers. Regular use, in other words, skews more senior than the sample as a whole.

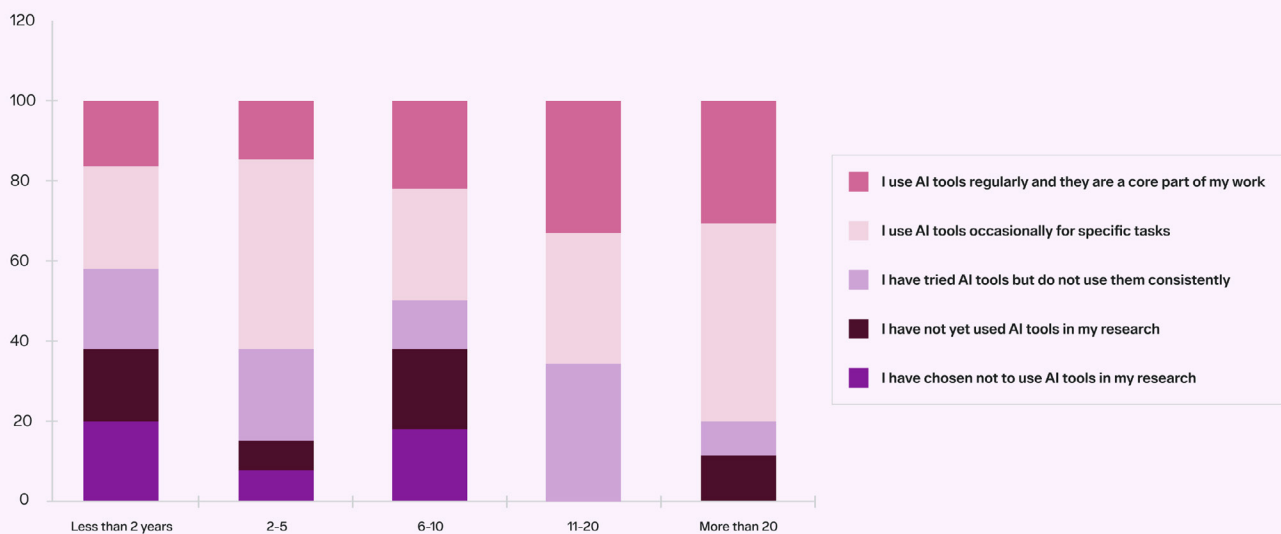
Key insights:

- **57% of researchers already use AI**—21% regularly, 36% occasionally.
- **Regular AI use rises with experience:** 33% of researchers with 11–20 years in the field are regular users, compared with 30% of those with more than 20 years and 25% of those with 6–10 years.
- **50% of regular AI users are academic researchers**—a majority, despite doctoral researchers being the largest group in the sample overall (33% of regular users).
- **Researchers with less than 2 years of experience make up a disproportionate share of both non-adopter groups:** 44% of all those who haven't tried AI yet, and 50% of all those who have chosen not to use it.
- **Healthcare shows the lowest overall AI adoption of any sector** in the sample: 58% of healthcare respondents have either not yet used AI or have chosen not to use it.

How researchers describe their current use of AI



Regular AI use by years of research experience



How researchers are using AI today

Two themes stood out most clearly in how researchers described their own use of AI: as a **research support or thinking partner**—helping brainstorm, structure ideas, and clarify thinking—and as a **writing assistant**, most often used to paraphrase or simplify dense material.

Those roles line up with where AI actually gets used. When combining regular and occasional use, literature review sees the highest AI use (71%), followed by transcription and data preparation (58%); interpretation and sense-making, the most analytically demanding stage, sees the least, at just 38%.

Researchers with 2–5 years' experience accounted for the largest share of positive-use mentions across writing, research support, coding, literature review, and transcription combined.

Key insights:

- **Literature review** sees the highest combined AI use (71%); **interpretation and sense-making** the lowest (38%).
- **Research support/thinking partner and writing assistant** were the two most frequently coded positive-use themes overall.
- **Doctoral researchers**: most associated with AI as a writing assistant.
- **Government/public sector researchers**: most associated with AI as research support and transcription.
- **Applied/industry researchers**: most associated with AI for coding and thematic analysis.

On AI as a research support or thinking partner:

“AI helps me a lot to do brainstorming, discussion and providing consideration. I also use AI to help me to define my thoughts clearer in English, since my first language is not English. However, the thing that I need to be cautious [about] is the AI hallucinations in providing the information.”

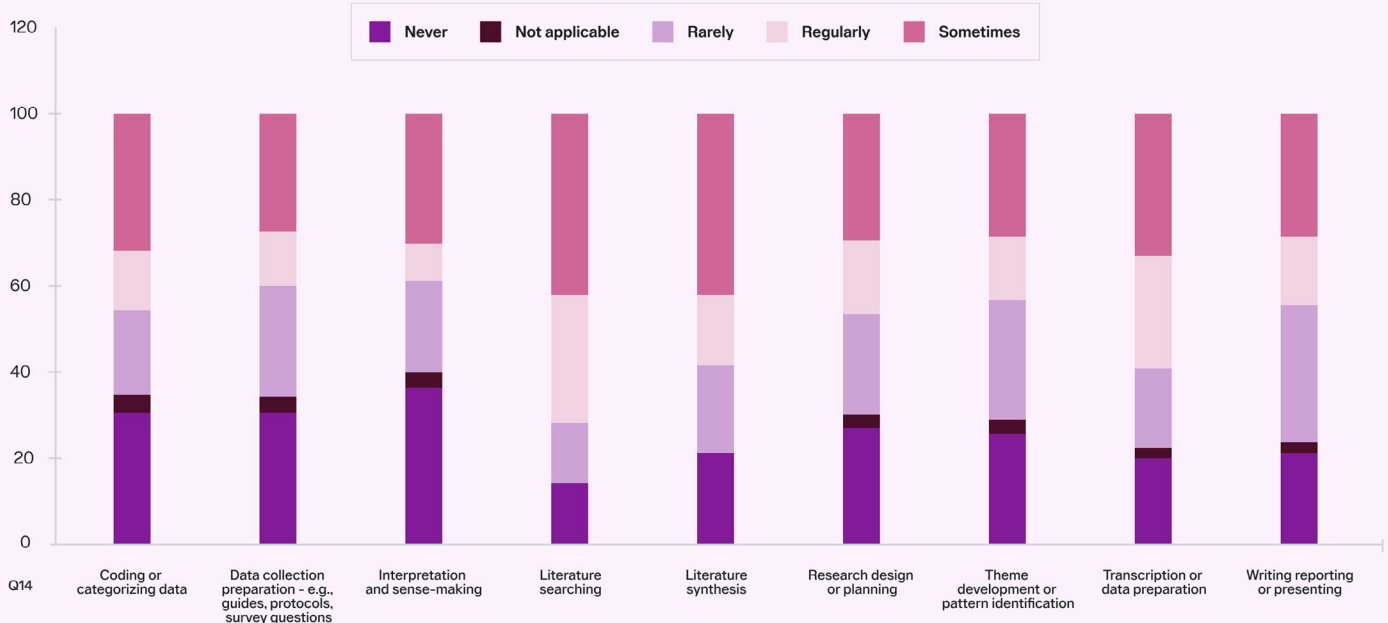
— Academic researcher—faculty, postdoc, or equivalent

On AI as a writing assistant:

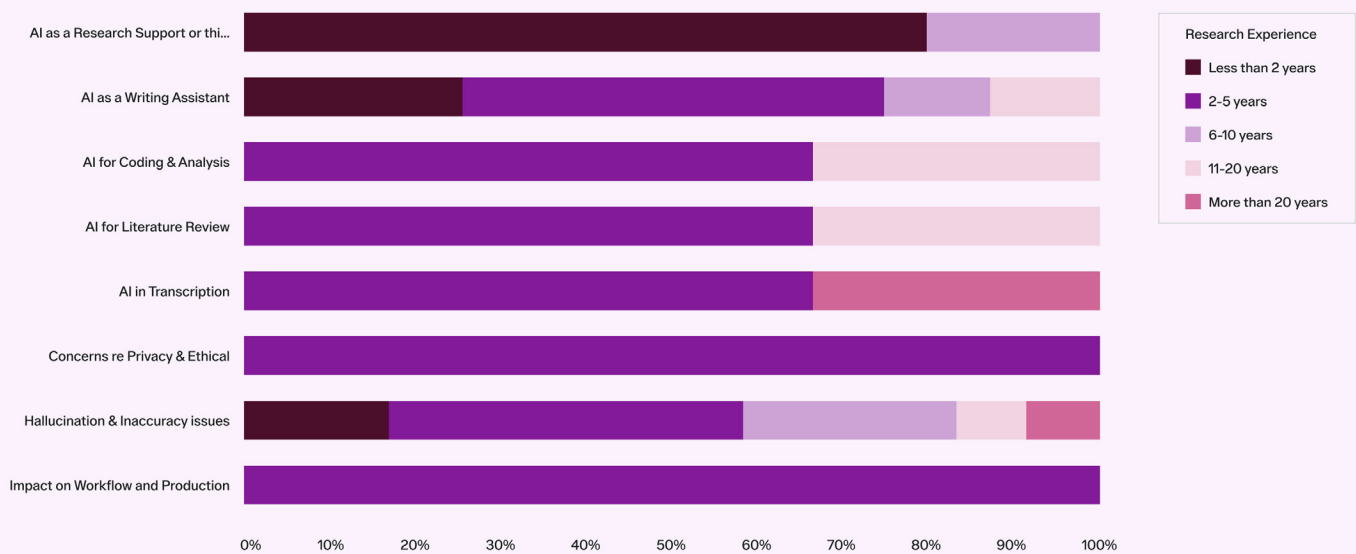
“Sometimes I read material that is too dense for me to understand. I ask AI to paraphrase into words that are simple.”

— Doctoral researcher / PhD student

Where in the research process AI gets used



AI use experiences by years of research experience



Where trust holds

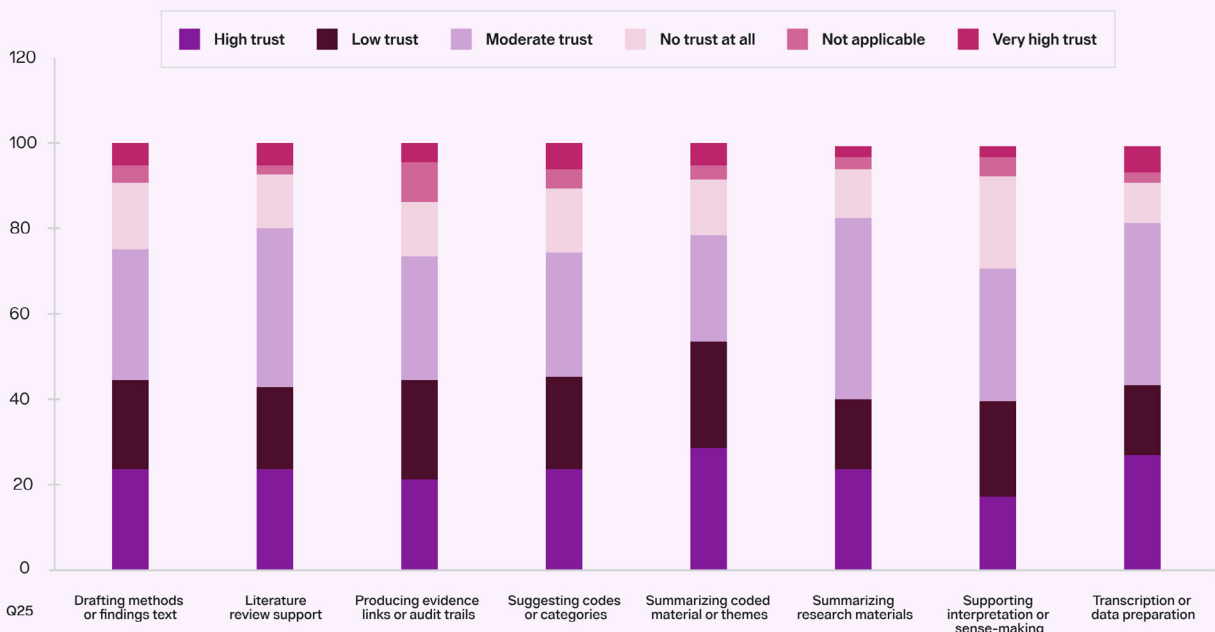
Where researchers reach for AI most is also where they trust it most. **For combined regular and occasional use, literature review sees the highest AI use (71%) and transcription the second-highest (58%).** Those same two tasks are exactly where trust in AI-generated outputs runs highest too: 34% report high or very high trust in AI for summarizing coded material, and 33% for transcription or data preparation. Interpretation and sense-making, the task researchers hand to AI least (just 8% regular use), is also the task they trust it with least (20% high or very high trust).

That's not a coincidence—it's the same instinct showing up twice, once in behavior and once in stated trust. Transcription and data preparation stands out as the clearest case: it's the one task in the survey where trust in AI's output outweighs distrust, making it the closest thing to a settled, comfortable use case researchers described.

Key insights:

- **Trust in AI-generated outputs is highest for summarizing coded material (34%) and transcription (33%)**—the same two tasks that see the heaviest actual use.
- **Transcription and data preparation** is the only task where trust outweighs distrust on balance; every other task tested skews toward distrust.
- **Trust concentrates on the same two tasks researchers already lean on AI for most**, showing usage and confidence moving together rather than independently.

Trust in AI-generated outputs, by research task



Where trust breaks down

That narrow pocket of trust doesn't offset the concern underneath it. **Distrust outweighs trust in seven of eight tasks tested; transcription and data preparation is the exception.** And the concern runs deeper than task-level skepticism: 87% of researchers are concerned or very concerned about accuracy and hallucination risk, 86% about research integrity, and 85% about data privacy—the three highest, most tightly clustered concerns in the survey. Yet when asked what's actually limiting their AI use in practice, distrust of outputs tops the list (57%), ahead of privacy and data security (51%), cost, or training gaps—concern is broad, but distrust of the work itself is what holds researchers back most.

Concern isn't spread evenly across the field, and one group stands out across nearly every category: doctoral researchers. They're named alongside academic and independent/consultant researchers as particularly evident on accuracy, and trust issues; alongside academic researchers specifically for hallucinations and misleading outputs; and on their own for privacy and ethical concerns, where they also accounted for the largest share of responses relating to prompting and learning challenges and data management challenges. Government and public sector researchers were particularly represented in data management, prompting and learning, and utility and functionality limitations.

Key insights:

- **Concern clusters around three issues:** 87% of researchers are concerned or very concerned about accuracy and hallucination risk, 86% about research integrity, and 85% about data privacy.
- **Distrust outweighs trust in 7 of 8 research tasks tested;** transcription and data preparation is the exception.
- **57% cite distrust of AI outputs as their top barrier to greater use,** ahead of data privacy and security, cost, or training gaps.

On hallucination and fabricated information:

"Trying to gather relevant literature for a lit review, used Copilot. It fabricated sources that did not exist and even fabricated hyperlinks. When I told it it was fabricated, it apologized and then provided more fabricated sources."

— Independent / consultant researcher

On AI inventing information not present in the source data:

"AI hallucinations. If it does not have the answer it will make something up, even when given a limited amount of data, told to only use / compile information given, it still adds information that does not exist."

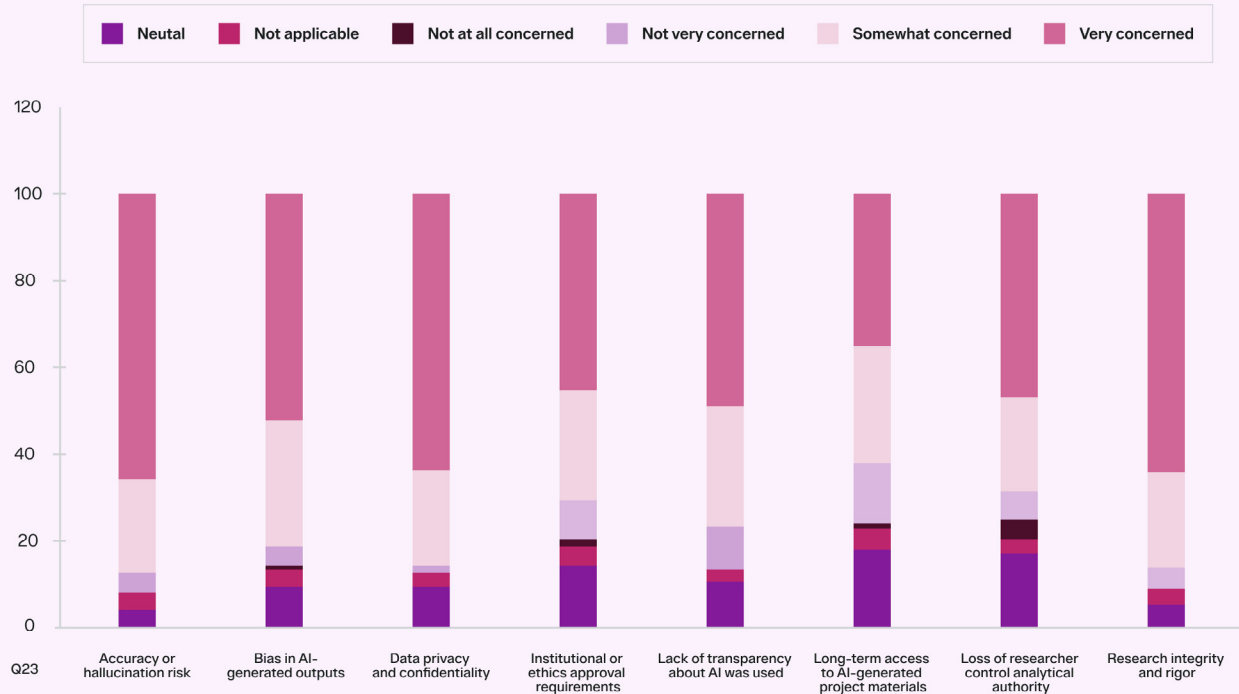
— Research support / librarian / methodologist

On data privacy concerns:

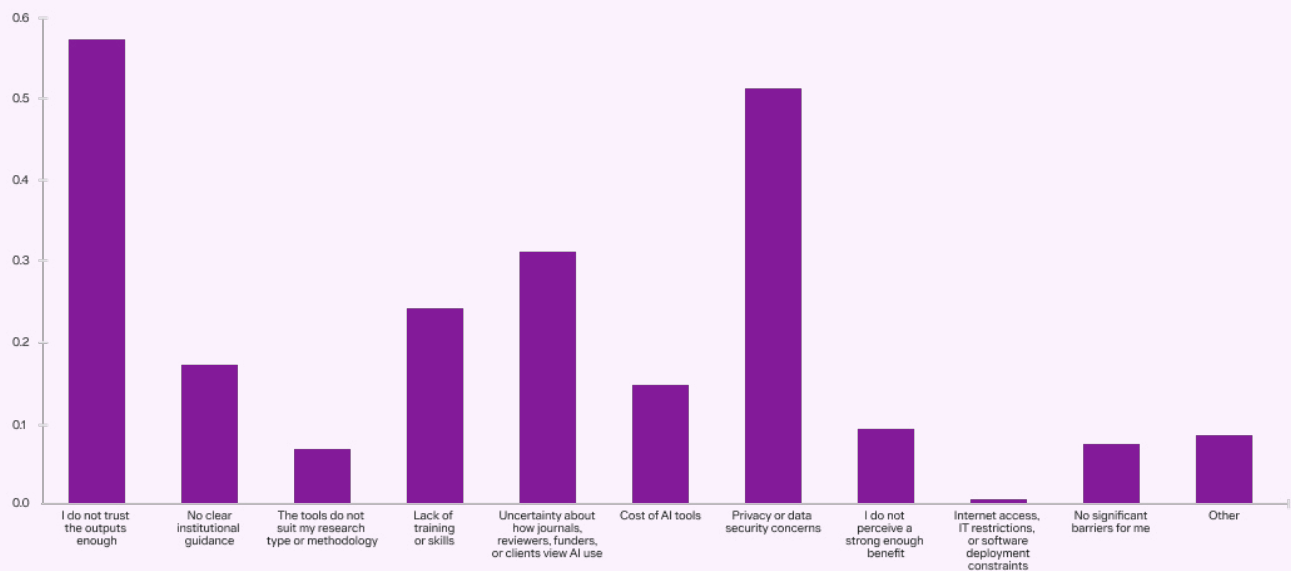
"I use ChatGPT. The upside is that it streamlines the workflow, especially for high-volume data. The negative is that, despite the terms and conditions, I have privacy concerns."

— Doctoral researcher / PhD student

What researchers worry about most when using AI



What is actually holding researchers back from using AI



The conditions for trust

Given where trust breaks down, researchers were direct about what would change that. Several themes stood out, each pointing to a different layer of the gap between AI's current capabilities and what research demands of it.

The most consistent ask was for verification built into the tool itself—researchers want AI-generated findings backed by visible evidence and traceable to source material, not asserted on faith. Close behind was a call for human oversight as a structural rule rather than an individual habit: AI treated as a first draft or second opinion, with a human required to confirm before anything counts as a finding. Clearer institutional guidance and stronger data privacy guarantees rounded out the list, often specifically framed as an approved, vetted list of AI tools rather than an open-ended policy.

Together, these asks describe something more specific than “better AI”—they describe rigor as a built-in feature, not an added responsibility for the researcher to carry alone. Researchers have, in effect, already written the requirements. What has been missing is a tool built to them.

Separately, when asked what would need to change in the AI tools, policy, or their field more broadly, a smaller group raised something more fundamental than a feature request—moral and environmental objections to AI as a category, separate from how well any given tool performs. One respondent, a doctoral researcher, put it plainly: they didn't see their objections changing “until major environmental and economic issues are addressed.”

Key insights:

- **Verification and traceability**—AI-generated findings backed by visible evidence, checkable against source material—was the most frequently requested change.
- **Human oversight as a structural rule**—AI treated as a first draft requiring confirmation, not a final answer—was another consistent theme.
- **Clearer institutional guidance and an approved tool list** were frequently requested, alongside stronger data privacy guarantees.

On checking and verifying AI output:

“More supporting evidence presented in responses. i.e., ChatGPT may say ‘I found this theme,’ but I would want to see examples to support that conclusion.”

— Doctoral researcher / PhD student

On human oversight and AI's proper role:

“AI output treated as a first draft or second opinion, never a final answer, especially for interpretation, coding qualitative data, or synthesizing literature. A clear rule: AI can suggest, a human must confirm.”

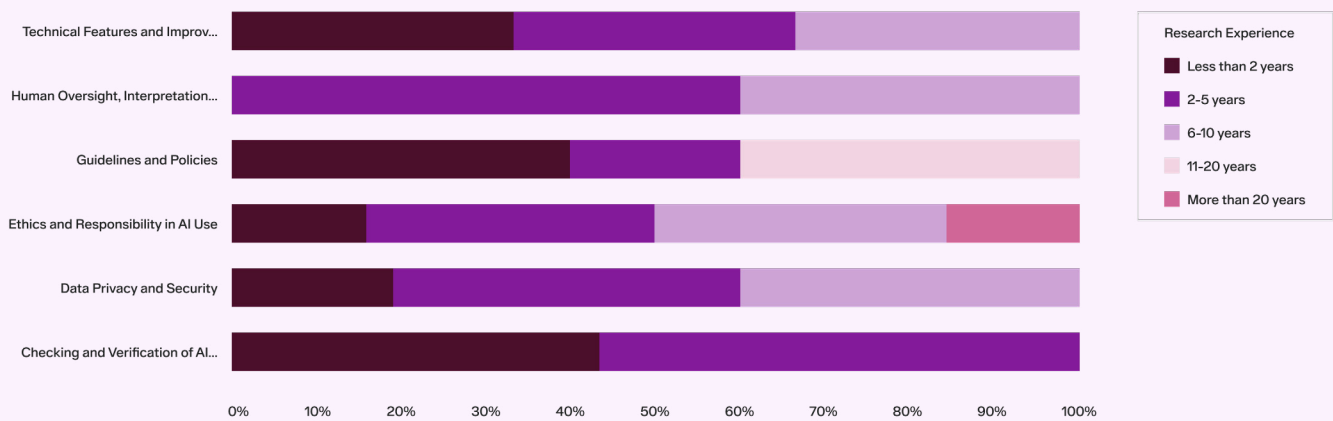
— Independent / consultant researcher

On data privacy and institutional guidance:

“I feel like privacy is key. It would be helpful if universities, institutions, etc., had an approved list of AI tools and how they may be used.”

— Doctoral researcher / PhD student

What researchers want from AI, by years of research experience



Policy, disclosure, and oversight

Institutional policy exists more often than confidence in AI does. 70% of researchers report their organization has some form of AI policy—38% specifically permit use with disclosure or review requirements—but policy clarity hasn't fully translated into consistent adoption. Among researchers who've tried AI without adopting it consistently, the largest share—45%—work at institutions with restrictive AI policies, more than double any other policy type.

Disclosure practices vary just as widely. About half of AI users say they disclose it “always” or “when required,” while a smaller share say they don't disclose it at all. Where formal disclosure is inconsistent, personal verification is not.

The large majority of researchers manually review AI output against source data or cross-check it against their own independent analysis. That same pattern extends to how researchers think AI should function at all: most believe it should generate suggestions for a human to review and decide on, a view that grows even stronger among researchers with direct experience using it.

Key insights:

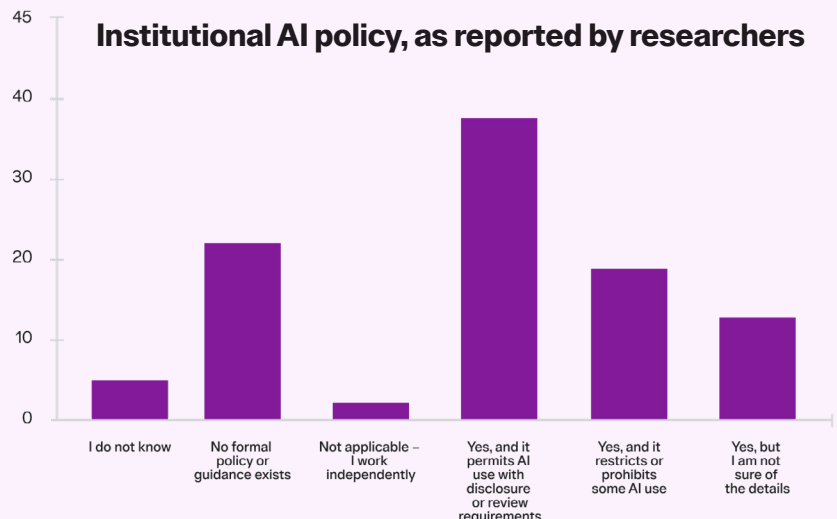
- **70% of respondents report their institution has some form of “yes” AI policy;** 38% specifically permit use with disclosure or review requirements.
- **51% of AI users disclose its use “always” or “when required”;** 10% report they don't disclose it at all.
- **61% manually review AI output against source data;** 59% cross-check against independent analysis; only 1% don't validate formally.
- **48% believe AI should generate suggestions for human review only,** rising to 71% among current AI users.

On why disclosure matters:

“Disclosure is key, and so is the ethical use of AI without infringing on the rights of others.”

— Research student—
undergraduate or master's

Institutional AI policy, as reported by researchers



A closer look: Non-academic and commercial research

Government agencies, healthcare organizations, and commercial research settings were examined together as a non-academic segment, separate from the broader academic-dominated sample. Usage here leans occasional rather than routine: 35% use AI for specific tasks now and then, and another 24% have tried it without settling into consistent use.

The same three groups also surfaced in the broader qualitative coding, where their described experiences and concerns diverged by setting:

- **Government and public sector respondents** most often described AI as a thinking partner and for transcription, and centered their concerns on ethics and responsibility—consistent with what they said would need to change: ease of use, accuracy, and privacy.
- **Applied and industry researchers** focused their use on coding and thematic analysis, and their concerns on checking and verifying AI outputs before trusting them, with institutional policy topping their list of needed changes.
- **Independent and consultant researchers** raised the most questions about data privacy, human oversight, and where the AI-powered tools themselves fall short, and pointed most to appropriate use and methodological considerations as what would need to change.

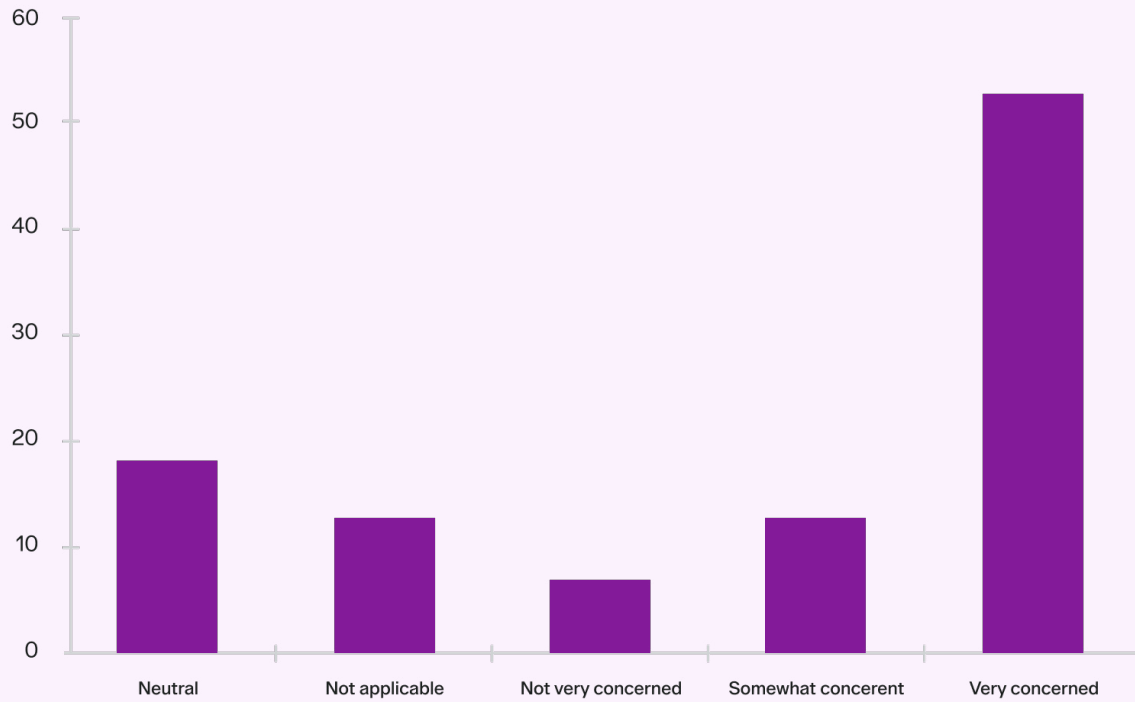
Data privacy tells a more layered story here than the headline concern suggests. General concern about privacy and confidentiality runs lower than the overall sample—65% somewhat or very concerned, versus 85%. But satisfaction with how their own tool actually handles data privacy and security is far less settled: only 25% are very satisfied, and the largest group (35%) is neutral.

Key insights:

- **35% of the combined non-academic segment use AI occasionally for specific tasks;** 24% have tried AI without using it consistently.
- **Positive AI experiences vary by setting**—government/public sector respondents point most to AI as a thinking partner and for transcription; applied/industry respondents to coding and thematic analysis.
- **65% of this segment are concerned or very concerned about data privacy** and confidentiality in general, compared with 85% in the overall sample.
- **Distrust of AI outputs remains the most frequently cited barrier to greater use,** consistent with the broader sample.

Note: Given the limited size of these groups, findings here are indicative rather than statistically representative.

Data privacy concern among government, healthcare, and commercial researchers



The bottom line: Adoption without confidence

Across every section of this survey, two numbers sit next to each other: 57% of researchers already use AI, and roughly 9 in 10 are concerned about the accuracy, integrity, or privacy of what it produces—87%, 86%, and 85% concerned about each in turn. This isn't a contradiction in the data—it shows up within the same respondents, often in the same sentence of an open-ended answer.

The pattern holds at every level of analysis. **Trust is highest for tasks that are easy to verify and lowest for the interpretive work at the center of qualitative analysis.**

Distrust of outputs, not cost or training gaps, is the most-cited reason researchers don't use AI more—a finding that holds in the general sample and, at a lower intensity, in government, healthcare, and commercial settings too.

Where formal governance is inconsistent, informal verification isn't: researchers check AI's work against source data themselves or cross-reference it against their own analysis. And when asked directly what would change their minds, **researchers didn't ask for less oversight—they asked for more, built into the tool itself: visible evidence, traceability, a human required to confirm before anything counts as a finding.**

The bottom line: researchers have not been waiting for permission to use AI. They've been supplying the rigor it lacks—manually, inconsistently, and alone. That's not a sustainable division of labor. It's a gap that needs to be closed by the tool, not the researcher.

Rigor by design: What this means for the field

Not every use of AI carries the same risk. A researcher using AI to draft an interview guide is taking on very little; a researcher relying on AI to surface a theme, with no way to trace it back to the data, is taking on a great deal. What researchers in this report are asking for isn't rigor performed despite the AI tool—it's rigor the AI tool helps put on the record.

The findings in this report set a bar, and we at Lumivero intend to be measured against it.

For more than three decades, researchers have trusted our research software to hold the infrastructure of rigor: audit trails, transparent coding, a defensible chain of evidence from raw data to finding. As we bring AI into that same environment, we are holding it to the same standard the researchers in this report demand of it—transparency into how every output was produced, a clear path from any suggestion back to the source material, and a human decision required before anything becomes a finding.

We are building AI that answers to the researcher, not the other way around. The costs this report documents—hours spent verifying by hand, rigor performed invisibly in side documents, institutions restricting what they cannot audit—are design problems, and we are treating them as ours to solve. Researchers should never have to choose between speed and rigor; our job is to build software where that choice never comes up.

You bring the judgment. Our job is to keep the record.



Explore NVivo AI Cloud

Learn more about NVivo AI Cloud—AI-powered research software built to keep your judgment on the record.

[Learn more →](#)

Appendix: Analysis methodology

Sample. This report is based on a survey of 115 researchers, academics, practitioners, and students engaged in qualitative or mixed methods research, examining current AI adoption, tool use, trust, and governance practices. The survey combined closed-ended questions, analyzed quantitatively, with open-ended questions on memorable AI experiences, frustrations, and desired changes, coded thematically. The survey was fielded from June 25, 2026 to August 14, 2026.

Sample composition. Doctoral researchers and PhD students made up the largest group (43 respondents), followed by academic researchers—faculty, postdocs, or equivalent (35 respondents). The sample skewed early-career: 32% reported less than two years of experience conducting, supporting, or supervising qualitative research. Geographically, the sample leaned toward North America (39%), followed by Europe (22%) and Asia Pacific (18%).

Variable base sizes. Not all questions were presented to or answered by the full sample. Two questions cited in this report were shown only to relevant sub-groups: “Which AI tools do you currently use in your research?” applied to 87 respondents who had used AI tools; “What is the primary reason you have not used AI tools in your research?” applied to 28 respondents who had not used AI tools. Percentages for these questions are calculated against their respective sub-group base, not the full sample of 115.

Non-academic and commercial addendum. A commercial and public-sector addendum separately examined three sub-segments: government or public sector agencies, healthcare organizations, and market/UX research. Given the small sample sizes, these sub-segment findings should be treated as indicative rather than statistically representative—this caveat should be retained anywhere these figures are cited.

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Written and edited by: Abigail Jacobsen, Senior Content Marketing Manager, Lumivero

Tool citations:

Lumivero (2026). XLSTAT statistical and data analysis solution. <https://www.xlstat.com/en>

Lumivero (2026). NVivo qualitative data analysis software. <https://lumivero.com/products/nvivo/>

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