

## The Explosion of AI-Powered Research Tools Is Reshaping UX Practice

**Jeffrey L. Sokolov, PhD**  
Design Researcher in  
Healthcare and Complex  
Systems  
Lexington, MA, USA  
jsokolov@yahoo.com

### Introduction

I begin with the premise that the explosion of AI-powered UX research tools is reshaping both the role of the researcher and the practice of UX research. In this essay, I examine three interrelated shifts: researchers moving from being hands-on investigators to workflow orchestrators; the tension between increased speed and scale and the risk of fragmented insight across disconnected tools; and the growing role of AI in shaping interpretation by surfacing patterns and themes early in synthesis.

Potential benefits to using AI-powered research tools include speed, efficiency, rapid iteration, and increased scale. There is a body of evidence suggesting that automated transcription and note-taking are beneficial, including one by Koesten that reported improved interview depth through enabling moderators to focus on expert reasoning rather than on documentation (Koesten, 2021; Costa et al., 2025).

At the same time, several risks have been reported, including inaccurate and incomplete answers delivered with a false sense of fluency. For example, a study published by Johnson (2025) uncovered a relationship between high degrees of automation and a decline in knowledge quality. As researchers, the key question we must ask ourselves is whether this is a natural result of transformative change or something else. Having spent most of my career either executing research on AI-powered tools or using AI-powered tools to conduct research, I believe we are in the midst of an accelerated transformation and that it is incumbent upon us to adapt.

Note that, in this essay, I avoid mentioning specific UX research tools, except for the class of AI chatbots such as ChatGPT and Claude™; doing so fairly or comprehensively is beyond the scope of this essay.



## The Explosion of AI-Powered UXR Tools

Over the last 5 years, there has been an explosion of UX research tools, with a growing number featuring AI capabilities. This was demonstrated by the annual tools survey conducted by User Interviews, which reported 100 tools in 2021, over 530 tools in 2024, and a navigable list of nearly 800 tools in 2026 (Balboni, 2023; Balboni, 2024; Phillora & Webber, 2026). More relevant to this essay, Ben Wiedmaier (2026) from User Interviews also recently published another map that included 30-plus AI tools.

Similarly, although I could find no definitive source for the growing market size in dollars, there are reports that the market has grown 2–3 times over the last decade, from approximately \$130 million in 2015 to approximately \$245–362 million in 2024, and finally to \$470 million in 2025; adoption of AI tools by UX researchers has grown from 20% in 2023 to 50% in 2024, and is projected to grow a whopping 80% in 2026 (Balboni, 2023; Balboni, 2024; Phillora & Webber, 2026). This increase in adoption is happening across the research workflow: Respondents report using AI tools for analyzing user research data (62%), transcription (54%), generating research questions (48%), and synthesis and reporting (45%) (Phillora & Webber, 2026).

An anecdotal indicator of this growth is the number of vendor emails I now receive daily from existing vendors, pointing me to new features or educational tutorials, or from new vendors promoting their applications. In the span of one 10-day period, I recently received 27 such emails.

## Researchers Are Moving From Hands-on Investigators to Workflow Orchestrators

Before this transformation, researchers performed every step in their workflow process, including planning, executing, analysis, and reporting, either by hand or with the benefit of traditional computer tools. However, with the availability of AI-powered UX research tools, many researchers are moving from working hands-on to orchestrating each step in the workflow using a best-of-breed stack of AI-powered tools.

AI is no longer seen as merely a supportive tool but increasingly as an active partner in different stages of the research process, from data collection and transcription to coding, thematic analysis, and reporting (Costa et al., 2025). In this new paradigm, researchers' focus has shifted from writing and validating their own analyses to understanding and evaluating the analyses generated by AI assistants (Gu et al., 2024). The most automated example of this transformation is in spec-driven agentic workflows in which the research is performed through a sequence of agent-based tasks codified in the spec-driven tool of choice (such as Claude Code).

To accommodate this new approach, researchers must acquire foundational skills in AI to operate the tools effectively and to evaluate AI-derived findings through a critical and ethical lens (Costa et al., 2025). In a world where AI can synthesize data, verification becomes an increasingly important skill. Koesten et al. (2021) listed the ability to generate test cases and check the results among these skills. In an early study of how these skills develop, Gu et al. (2024) examined how data analysts evaluate AI-powered analyses. In their study, data analysts often started their verification workflows focusing on procedure-oriented behaviors (answering "what did the AI do?") and only shifted to data-oriented behaviors (answering "does the [resulting] data make sense?") once they noticed issues in the AI-generated output. This ability to move between inspecting how the AI works and determining whether the data results are coherent is an example of a skill that will be beneficial to UX researchers moving forward.

The metaphor of an orchestra conductor also helps guide the productive use of AI tools. For UX researchers, several relevant aspects of effective orchestration include

- defining the process from identifying the right problem to converging on the right solution;
- identifying the data necessary to facilitate stakeholder decision-making;
- operationalizing the research questions as prompts or instructions, which then become part of the documented methodology;
- clearly framing and constraining the AI to deliver output needed for the next step, and

- evaluating the accuracy and completeness of the AI output and iterating on the analyses.

Before addressing the question of fragmented tools, I want to highlight one useful, perhaps unexpected, advantage. With the rapid iterations enabled by AI-powered UX research tools, researchers can view AI-assistance as a starting point to help guide subsequent analyses. Researchers can poke and prod the data, looking for interesting directions to pursue. For example, in my explorations with synthetic users, I ran a study in which I created highly anxious compliance professionals and asked them several questions about how they would deal with the anxiety-provoking situation of coming to work and finding that their boss started requiring them to use a specific AI tool. This is something I could not do with human subjects, and prompting AI for it helped provide ideas for enablement and training.

### **Growing Pains Leave Researchers With Insights Scattered Across a Set of Fragmented Tools**

Although market size and adoption of AI-powered tools are growing, the field is also in a constant state of flux. Vendors often begin by optimizing one aspect of the UX research workflow, such as recruiting or transcription, then realize they must expand left (toward discovery) or right (toward evaluation) to remain competitive. There are also emerging tool categories like AI-moderated interviewing and synthetic users that are just beginning to feel this pressure.

Agentic AI is a significant forcing function, providing a means of automating agent orchestration across predefined workflows. Vibe coding, or spec-driven development using Claude Code, for example, offers a completely automated and AI-driven workflow that includes market analysis, synthetic users, foundational research (such as the jobs to be done), prototyping, and finally validation.

The modern UX researcher must coordinate a cacophony of tools into a coherent workflow. I consider the increasing availability of purpose-built UXR tools a tremendous opportunity overall, but the impact of the current state of fragmentation is significant.

First, data are initially spread across multiple applications. The tool that assists with participant recruiting might be the initial collection point. Or the tools that facilitate qualitative data analysis might, in fact, fill that need. Second, insights derived from synthesis, either human- or AI-powered, are scattered across different tools. The recruiting tool adds data tagging as a feature, for example. Various document management tools also store final reports in different places. Third, integration between these different tools, for example, automatic transfer of interview recordings, is inconsistent and exists only in early betas or product roadmaps. Some of the tools that move data between systems are fragile, whereas others, such as MCP servers, require development skills. Fourth, researchers are forced to devise or conform to formats that make the output of one tool acceptable to the input of a different tool. Finally, our business stakeholders (both product management and engineering), who are not skilled or trained to use these tools, are then asked to continually adapt to searching for actionable results across a dizzying array of unfamiliar tools.

### **The Growing Sensemaking Role of AI in the Synthesis of Qualitative Data**

In the previous sections that discuss UX research as workflow orchestration, I focus on changes to research processes. In this section, I wish to focus on the growing role of AI in shaping data synthesis.

We are just beginning to learn how to effectively and ethically leverage AI to assist in the synthesis of qualitative data, for example, moving from naively uploading a tranche of transcripts and asking the AI to simply summarize them, or more sophisticatedly, being direct and intentional about the business questions at hand.

In my own research workflow, I move seamlessly between inductive and deductive reasoning, heavily influenced by business goals and timeframes. I review a transcript and note different themes as an inductive exercise—like the commenting phase of grounded theory—before moving to the coding phase, which assigns meaning to what participants say and do. In

addition, since UX research in the corporate world is always motivated to find answers to specific questions, there is always a deductive component to the exercise. In my situation, I work in a large enterprise with a global research team. Over time, several cross-project and enterprise-relevant questions have been codified in various metadata and tagging templates, for example, questions about how knowledge workers manage the pace of regulatory change cuts across many projects and divisions. I would still like to maintain this flexibility as I move to incorporate AI into my practice.

It raises several questions: What is the significance of delegating some or all of this to an AI? Does it matter if the initial inductive reasoning is delegated? What is the impact of providing the AI with a pre-defined set of codes and examples? We know that AI is effective at identifying patterns but lacks the human capacity to interpret context, emotion, and culture. And, of course, we don't want to lose the aha moments that surface when we deeply experience the data. We don't want to lose "the function of codes as bookmarks, reminders, [and] entry points that help us return to meaningful fragments, compare similar insights, and build grounded interpretations" (Friese, 2026).

Further, we know from previous work in the social sciences that meaning is not solely created by one individual, but rather by social and organizational actors. How different would it be to co-create meaning with an AI? Put another way, how can we collaborate or orchestrate an AI tool to help make sense of the data and generate actionable results? This is a common theme in the trade and research literature these days: Costa et al. (2025) suggested inquiry be performed by a dynamic configuration of actors, both human and non-human, to co-produce knowledge outcomes.

If researchers must now organize a series of actions to be executed together with AI, I suggest that this new way of working might entail

- building a pipeline in which each subsequent instruction has a clear input, clear instructions, and a clear output;
- providing enough context in the right sequence so that the AI can focus on the specific sensemaking needed at each step;
- developing prompts that minimize hallucinations or exaggerations and maximize specificity, accuracy, and completeness;
- extracting and describing themes with supporting quotes and hierarchical categories;
- verifying that the quotes are verbatim, not fabricated, and meaningfully classified under an assigned code; and
- ensuring traceability and verification along the way, so researchers can audit which data were used to calculate the answer.

Researchers have already begun exploring techniques to improve the orchestration of AI sensemaking. For example, Xiao et al. (2023) demonstrated that providing an AI with a human-defined codebook and examples improves accuracy. Similarly, Hou et al. (2024) reported that fine-tuning a Large Language Model with many examples increases reliability. And Koesten (2021) suggested that AI-powered research tools should surface explicit features that make it easy for researchers to inspect the AI procedure when they notice an issue or anomaly.

Finally, if humans are tasked with directing and verifying the AI's sensemaking activity, it follows that expertise in the subject domain—as well as the underlying AI technology—matters. Koesten (2021) reported that (a) experienced data analysts are more vigilant and (b) the ability to identify an issue and then review how an answer was derived is correlated with expertise. She further suggests that humans are needed to place data interpretation within broader contexts. Gu et al. (2024) wrote that data analysts need to inspect the data (such as for data quality, format, columns, and values) and engage with the data (for example, understanding the relationships between columns and looking for outliers, etc.) as part of their data sensemaking activities.

## In Closing

The rapid expansion in the availability of AI-powered research tools is triggering immense change in research practices. In fact, this is happening so rapidly that, if I were to write this essay a year or even 6 months from now, I would expect a lot to have changed. AI is no longer peripheral to the way we work; it is embedded across the entire research lifecycle.

Several metaphors have been proposed to describe the ideal human-AI collaboration. For example, Friese (2026) proposes a model in which AI helps surface relevant data in response to carefully crafted questions. She describes this as a distributed and co-constructed model of knowledge creation.

Rather than viewing AI as a co-pilot or co-creator, I view the interaction similar to that of the conductor-orchestra relationship. The human will act to unify any number of AI-powered tools to ensure a valid, ethical, and defensible result. In this model, human researchers necessarily update their practice to accommodate AI's strengths and weaknesses at a given moment in time. Humans will be tasked with mapping out the end-to-end process and following it through to the end. It conceptualizes the power of triangulation as (a) intentional variation in evidence across sources, methods, and interpretive roles, and (b) integration as the explicit linking of datasets, analyses, and inferences to produce results.

Human researchers are starting to devise and adhere to a growing set of practices for evaluating AI output that ensures alignment between the AI-generated outputs and the original research questions (Costa et al., 2025). These practices reduce hallucinations, ensure explainability, and establish audit trails.

Across the board, the studies I reviewed for this essay point to the importance of a hybrid approach in which humans manage the overall research process and make "interpretive, nuanced judgments" (Johnson, 2025). Johnson and others (for example, Koesten, 2021) have explored the importance of human expert involvement and manual cognitive processes to achieving higher value and improving accuracy in AI-powered user research. AI will not replace UX researchers, but it will reshape the practice around orchestration, verification, and judgment. I encourage my fellow researchers to inspect and refine these techniques and to share their results with the broader community.

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- exploring the conceptual and rhetorical space around the explosion of AI-powered tools;
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## Further Resources

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## About the Author



### **Jeffrey L. Sokolov, PhD**

Jeff Sokolov is a Design Researcher in Healthcare and Complex Systems. Over the past decade, he has conducted research across healthcare and fintech to inform product decisions. His work focuses on how people learn to use digital tools, find and interpret information, and make decisions over time, translating these insights into data-informed choices for product teams. He holds a PhD in Cognitive-Developmental Psychology from Carnegie Mellon University and a BA in Experimental Psychology from the University of California, San Diego.