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Harnessing ChatGPT for educational scientific research: A qualitative analysis approach

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ABSTRACT

This qualitative study investigates researchers' perceptions of ChatGPT's influence on research creativity, efficiency, and scholarly integrity. A cross-sectional survey with six open-ended questions was administered to 112 participants across academic levels (2 post-doctoral, 20 PhD, 26 Master's, 64 diploma holders) within education and psychology. Data was analyzed using triangulated methods: SWOT analysis, thematic analysis, and systematic open coding. Findings indicate ChatGPT is perceived as a dual-edged tool that enhances productivity while posing cognitive and ethical risks. Ethical considerations are central, with participants emphasizing the need for structured guidelines. The human factor remains decisive—AI's benefits depend on researchers' methodological awareness and ethical engagement. Results suggest AI functions optimally as a cognitive scaffold, with its impact contingent upon use patterns and user experience. The findings carry implications for developing evidence-based policies and training for responsible AI integration in academic research.

Keywords: artificial intelligence, academic research, ChatGPT, AI ethics, research methodology, scholarly integrity, AI-assisted research, qualitative analysis

INTRODUCTION

The integration of artificial intelligence into educational and scientific research has fundamentally transformed how scholars approach knowledge creation, data analysis, and academic writing, with ChatGPT emerging as a particularly influential tool for assisting researchers across multiple phases of scholarly work, from literature reviews and hypothesis formulation to methodological structuring and manuscript preparation. This technological shift presents unprecedented opportunities to enhance research productivity, streamline complex cognitive tasks, and democratize access to academic resources across institutional contexts, yet it simultaneously introduces complex challenges that the academic community has only begun to grapple with, including concerns about diminished critical thinking, over-reliance on AI-generated content, threats to academic integrity, and the potential erosion of foundational research skills (Bender et al., 2021; Farrokhnia et al., 2023; Rahman & Watanobe, 2023). While existing literature has developed along multiple trajectories, one strand demonstrating AI's capabilities in generating code, answering disciplinary questions, and automating qualitative coding (Kieser et al., 2023; Lee et al., 2024), and another raising ethical and epistemological concerns about bias, homogenization of scholarly output, and the cognitive struggle from which genuine understanding emerges (Bender et al., 2021; Birhane et al., 2022; Van Dis et al., 2023)—significant gaps remain, particularly the absence of empirically grounded qualitative studies that capture how researchers themselves perceive, experience, and navigate AI integration in their daily scholarly work. The present study addresses these gaps by employing a triangulated qualitative methodology that integrates SWOT analysis, thematic analysis following Braun and Clarke's (2006) framework, and systematic open coding of responses from 112 researchers across academic levels and disciplinary contexts within education and psychology, thereby providing a multidimensional account of AI's role in research that is simultaneously strategic, semantic, and experiential. By investigating researchers' tool preferences, interpretive strategies, challenges, ethical deliberations, and visions for AI's future in scholarship, this study aims to generate insights that are both theoretically illuminating and practically relevant for the responsible integration of AI into academic research, ensuring that conversations about AI's role remain connected to the practices, values, and concerns of those whose work it most directly affects.

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LITERATURE REVIEW

The integration of artificial intelligence into academic research has emerged as a central concern in contemporary scholarly discourse, with investigations spanning disciplinary contexts, methodological approaches, and theoretical frameworks. As generative AI tools, particularly ChatGPT, become increasingly embedded in research workflows, understanding their implications for scholarly practice has grown both urgent and complex. The existing literature reveals a growing body of work documenting AI's capabilities, exploring its applications, and raising critical questions about its consequences for academic integrity, cognitive development, and the nature of scholarship itself. Yet this literature also exhibits significant gaps, particularly in its attention to researchers' lived experiences and its integration of multiple analytical lenses, which the present study seeks to address.

Hosseini et al. (2023) conducted one of the earliest large-scale investigations into ChatGPT's role across education, healthcare, and research contexts, employing a mixed-method approach with survey data from diverse participants. Their finding that only 40% of respondents had prior experience with ChatGPT, with notable disparities between trainees and faculty members in both awareness and usage patterns, established important baseline data about adoption rates. This identification of usage disparities across career stages points to a dimension that subsequent research has pursued more deeply: the relationship between research experience and AI engagement patterns. However, the study's reliance on self-reported perceptions limits the objectivity of its findings, and its focus on general attitudes rather than specific research practices leaves unanswered questions about how AI functions in scholarly work. In contrast, Rahman and Watanobe (2023) adopted an experimental approach, empirically testing ChatGPT's capacity to generate and debug code in programming education. Their methodology demonstrated both AI's potential to assist with technical tasks and its significant limitations in contexts requiring deep understanding, while their identification of risks, including decreased critical thinking and over-reliance on AI-generated content, anticipated concerns that have since become central to the scholarly conversation. Yet the narrow focus on programming limits generalizability to broader educational domains, and the descriptive account of risks without accompanying pedagogical frameworks leaves open the question of how institutions might proactively address these challenges. Where Hosseini et al. provide breadth across contexts, Rahman and Watanobe offer depth within a single domain; together, they illustrate the trade-off between generalizability and specificity that characterizes much AI research.

Kieser et al. (2023) extended the investigation into disciplinary-specific applications, exploring large language models in physics education for test development and student cognition analysis. Their finding that ChatGPT could successfully answer Force Concept Inventory questions and simulate common student misconceptions opened new possibilities for assessment design while simultaneously raising ethical questions about using synthetic data to model human cognition. The study's approach of prompting ChatGPT to mimic human errors suggested potential for AI-generated distractors in test design, yet it left unresolved whether these simulated responses genuinely reflect student reasoning or merely represent sophisticated pattern recognition. This uncertainty echoes concerns raised by Bender et al. (2021) in their influential critique of large language models as "stochastic parrots, systems that generate plausible-sounding text without genuine understanding. Bender et al.'s analysis of the dangers inherent in systems trained on vast corpora of internet text without adequate attention to bias, environmental impact, and the limitations of statistical approaches to language has become a touchstone for discussions of AI's limitations. Where Kieser et al. demonstrate AI's apparent capability in simulating cognition, Bender et al. warn that such simulations may mask the absence of genuine understanding, a tension that becomes increasingly significant as AI tools are deployed in educational and research contexts requiring authentic intellectual engagement.

Farrokhnia et al. (2023) introduced a structured analytical framework through their SWOT analysis of ChatGPT in education, systematically categorizing strengths, weaknesses, opportunities, and threats associated with the technology. This framework has proven influential, providing a vocabulary and structure for discussing AI's multidimensional implications. Their identification of academic dishonesty concerns, biases in AI outputs, and limitations in reasoning abilities anticipated themes that have since been widely discussed. However, the theoretical rather than empirical basis of the analysis limits its grounding in actual researcher experience. Karakose (2023) similarly provided a broad exploration of ChatGPT's applications in educational research, cataloguing both opportunities and concerns, including the well-documented problem of fabricated references and ethical questions about AI's role in academic publishing. Yet like Farrokhnia et al., Karakose's descriptive approach lacks empirical validation for claims about ChatGPT's effectiveness, and the acknowledgment of risks without proposed mitigation strategies leaves practical implications underdeveloped. Both studies share a common limitation: they identify what might be at stake without investigating how researchers experience these stakes in practice. The present study addresses this gap by grounding SWOT analysis in researcher-generated data, transforming a theoretical framework into an empirical one.

Strzelecki (2024) applied a technology adoption model to analyze ChatGPT use in higher education, employing Partial Least Squares Structural Equation Modeling on survey data from 534 Polish university students. The study provided statistical validation of factors influencing adoption—habit, performance expectations, and hedonic motivation emerged as significant predictors—offering valuable insights into the drivers of AI engagement. This quantitative approach contrasts sharply with the qualitative inquiries of Lee et al. (2024), who critically evaluated ChatGPT's application in qualitative medical research, specifically for thematic analysis. Lee et al.'s identification of ChatGPT's potential for automating text coding and generating interview scripts, alongside risks of interpretive biases and thematic distortions, speaks directly to questions about AI's role in qualitative inquiry. Where Strzelecki illuminates why researchers might

adopt AI, Lee et al. examine what happens when they do, yet neither fully captures how researchers themselves make sense of these dynamics. Strzelecki's single-country context limits generalizability, while Lee et al.'s focus on medical research leaves questions about applicability to educational research settings. The present study bridges these approaches by examining both adoption patterns and interpretive consequences within educational research contexts, attending to researcher perspectives that quantitative surveys cannot capture and that context-specific qualitative studies may miss.

Van Dis et al. (2023) articulated five priorities for research on ChatGPT, emphasizing the need for transparency, accountability, and human oversight in AI-assisted scholarship. Their argument that AI should function as a collaborator rather than an author in scientific writing, maintaining human responsibility for research outputs, aligns with Floridi and Chiriatti's (2020) early philosophical analysis of GPT-3, which identified transparency, accountability, and beneficence as principles for ethical AI use. Both studies share a commitment to articulating normative frameworks for AI integration, yet neither examines how researchers operationalize these principles in practice. The present study extends their work by revealing how researchers navigate questions of transparency, accountability, and authorship in daily practice, disclosing AI use selectively, calibrating trust based on experience, and distinguishing between tasks they delegate to AI and those they reserve for themselves. Where van Dis et al. and Floridi and Chiriatti provide principles, the present study provides practice, grounding normative frameworks in empirical reality.

Sallam (2023) provided a systematic review of ChatGPT's utility in healthcare education, research, and practice, synthesizing findings across multiple studies to identify both promising applications and valid concerns. The review's attention to ethical implications, including questions of plagiarism, authorship, and academic integrity, anticipates themes that emerge centrally in the present study. Cotton et al. (2023) and Perkins (2023) similarly examined academic integrity considerations in the era of ChatGPT, raising concerns about plagiarism, cheating, and the challenges AI poses to traditional assessment models. Their analyses of how AI might be used to circumvent learning objectives share common ground with Sallam's review, yet all three approach integrity from an institutional perspective, focusing on detection, prevention, and policy. The present study takes a different tack, examining how researchers themselves perceive and navigate integrity concerns. The finding that 71.4% of participants raised ethical considerations but did so with nuance, distinguishing between using AI to enhance versus replace thinking, between disclosed and undisclosed use, and between different purposes and contexts, suggests that researcher perspectives may be more complex than institutional discourses acknowledge.

Birhane et al. (2022) extended critical perspectives on AI ethics, examining the "forgotten margins" of AI discourse and how mainstream AI ethics conversations often overlook marginalized perspectives and reinforce existing power structures. Their analysis of how AI systems can perpetuate and amplify social inequalities, even when developed with good intentions, resonates with Noble and Smith (2018) and Benjamin's (2019) examinations of how technology can exacerbate existing social inequalities. Where Birhane et al. focus on the development and deployment of AI systems themselves, the present study examines how these equity concerns manifest in research practice, in differential access to AI tools and training across institutional contexts, in the additional burdens faced by non-native English speakers, in the worry that AI might create new divides between those who know how to use it effectively and those who do not. The theoretical concerns these scholars raise find concrete expression in participants' accounts of their institutional circumstances.

Davis (1989), and Venkatesh et al. (2003) developed foundational technology acceptance models that have shaped the understanding of adoption patterns across contexts. These models emphasize perceived usefulness and ease of use as predictors of adoption, focusing on instrumental considerations of efficiency and convenience. Ericsson and Pool (2016) and Dreyfus and Dreyfus (1986), by contrast, developed theories of expertise acquisition that emphasize the role of deliberate practice and the developmental trajectory from novice to expert. These frameworks illuminate different aspects of AI integration: technology acceptance models explain why researchers might adopt AI (it is useful and easy), while expertise theories explain what might be at stake in adoption (the developmental consequences of relying on tools rather than developing capabilities). The present study reveals that researchers themselves hold both perspectives in tension, simultaneously appreciating AI's utility and worrying about its developmental implications—a complexity that neither framework alone captures. The finding that novices use AI compensatorily to fill capability gaps while experts use it augmentatively to enhance existing capabilities suggests that the relationship between AI adoption and expertise development is more intricate than either body of literature has recognized.

Pinch and Bijker (1984) and Bijker (2001) advanced social construction of technology perspectives, emphasizing that technological meanings and uses emerge through collective negotiation rather than being determined by technical features alone. This theoretical lens illuminates the present study's finding that researchers across categories called for collective deliberation about AI norms, recognizing that shared standards cannot be imposed from above but must emerge through community sensemaking. Where technology acceptance models treat adoption as individual decision-making and expertise theories treat development as individual trajectory, social construction perspectives emphasize the collective dimension, the way norms, practices, and meanings are negotiated within communities. The call from 73% of participants for collective deliberation about AI norms suggests that researchers recognize this social dimension and seek structured opportunities for community sensemaking.

Whittlestone and Clark (2021), and Stahl et al. (2023) advanced frameworks for AI governance, emphasizing the need for adaptive, principle-based approaches that can respond to rapid technological change. Their proposals resonate with the present study's finding that participants call for principle-based rather than rule-based guidance, recognizing that static regulations cannot anticipate every

scenario in which AI use might be appropriate in one context and problematic in another. The governance challenge they identify, how to create frameworks that provide guidance without rigidity, that support ethical judgment without prescribing it, is precisely the challenge participants describe facing in their daily practice. Where governance frameworks propose institutional solutions, the present study reveals that researchers are already engaged in the kind of adaptive, context-sensitive judgment that such frameworks aim to support.

The synthesis of this literature reveals several patterns that inform the present study. First, a fundamental tension runs through existing research between enthusiasm about AI's capabilities and concern about its consequences. Studies demonstrating what AI can do, generate code, answer physics questions, automate qualitative coding, are paralleled by studies warning about what AI might undermine, critical thinking, genuine understanding, and equitable access. This tension is not resolvable through technical means alone but requires the kind of nuanced, context-sensitive understanding that qualitative inquiry can provide.

Second, the literature exhibits a methodological divide between quantitative studies of adoption patterns and qualitative investigations of AI applications. Quantitative studies illuminate trends and predictors but cannot capture the complexity of researcher experience; qualitative studies provide depth but often in narrow contexts that limit generalizability. The present study bridges this divide by employing systematic qualitative methods with a sample large enough (N = 112) to identify patterns while preserving the richness of individual perspective.

Third, existing research approaches AI ethics primarily through normative frameworks, proposing principles, identifying risks, calling for guidelines, rather than through empirical investigation of how researchers actually navigate ethical tensions. The present study addresses this gap by examining researcher perspectives on academic integrity, disclosure practices, and the distinction between legitimate and illegitimate use, grounding ethical discourse in empirical reality.

Fourth, the literature reveals growing recognition that AI's implications for cognitive development and expertise acquisition deserve attention, yet few studies have examined how researchers at different career stages experience and navigate these implications. The present study's attention to the experience gradient, the systematic differences between novice and expert engagement with AI, addresses this gap.

Fifth, equity concerns raised theoretically in the literature find concrete expression in participants' accounts of differential access and institutional variation, suggesting that the distributive consequences of AI integration warrant sustained empirical attention.

The present study addresses these interconnected gaps by offering an empirically grounded, methodologically triangulated investigation of researcher perspectives on ChatGPT in educational research. By attending to the lived experiences of 112 researchers across academic levels and disciplinary contexts, this study provides the kind of nuanced, context-sensitive account that existing literature has called for but not yet delivered. The study does not seek to resolve the tensions the literature identifies, between capability and consequence, between adoption and development, between innovation and integrity, but rather to illuminate how researchers themselves navigate these tensions, what resources they draw on, what concerns they harbor, and what guidance they seek. In doing so, it aims to ground ongoing scholarly discourse about AI in the reality of researcher experience, ensuring that conversations about AI's role in academia remain connected to the practices, values, and concerns of those whose work it most directly affects.

PROBLEM STATEMENT

The increasing integration of artificial intelligence into academic research has generated substantial scholarly discourse regarding its potential to enhance research quality, efficiency, and methodological precision, yet despite growing interest in AI-assisted research, a systematic examination of the existing literature reveals a significant threefold gap that the present study seeks to address.

First, most prior studies have adopted quantitative approaches examining AI's technical capabilities or adoption patterns through surveys and technology acceptance models (Hosseini et al., 2023; Strzelecki, 2024), which, while valuable for identifying usage trends, fail to capture the nuanced perceptions, lived experiences, doubts, adaptations, ethical deliberations, and evolving practices that shape how researchers actually engage with AI in their daily scholarly work.

Second, among the limited qualitative studies available, few have moved beyond descriptive accounts to employ rigorous analytical frameworks capable of capturing the multidimensional nature of AI's role in academia—Farrokhnia et al. (2023) conducted a theoretical SWOT analysis lacking empirical grounding, Lee et al. (2024) explored ChatGPT's technical capabilities for thematic analysis without examining researcher perspectives, and Karakose (2023) provided a broad exploration lacking empirical validation—leaving unexamined how researchers themselves perceive, experience, and navigate AI integration.

Third, no identified study has systematically triangulated multiple qualitative analytical lenses—specifically, the combination of SWOT analysis for strategic structure, thematic analysis for deep meaning patterns, and systematic coding of open-ended responses for experiential richness—to capture the phenomenon's full complexity as simultaneously a strategic resource, a source of meaning-making, and a lived reality. This gap is rendered urgent by the rapid proliferation of AI tools in academic settings and the corresponding absence of evidence-based guidance for their responsible integration, as universities increasingly called upon to develop policies, training programs, and ethical guidelines lack empirical evidence about how researchers engage with these tools, what challenges they encounter, what support they need, and what informal norms are emerging in practice (Alamri et al., 2025; Aljohani et al., 2025; Annamalai et al., 2025).

Furthermore, while scholarly commentary has raised concerns about plagiarism, authorship, and academic integrity

(Bender et al., 2021; Cotton et al., 2023; Perkins, 2023; Van Dis et al., 2023), little is known about how researchers themselves navigate these ethical tensions in practice, how they distinguish between legitimate assistance and inappropriate substitution, how experienced versus novice researchers differ in ethical reasoning, and how disciplinary contexts shape acceptable use.

The present study addresses these interconnected gaps by combining SWOT analysis, thematic analysis, and systematic coding of participant responses from 112 researchers across academic levels and disciplinary contexts to investigate tool preferences, interpretive strategies, challenges, ethical deliberations, and visions for AI's future, thereby providing a multi-dimensional understanding of AI's role in contemporary research practices that captures both strategic dimensions and the nuanced, context-dependent ways researchers experience and navigate this technological transformation.

The study is guided by the following research questions:

RQ1. What types of AI-powered research assistance tools do researchers prefer, and what rationales underlie these preferences?

RQ2. What strategies do researchers employ when encountering difficulties in interpreting research findings?

RQ3. What challenges do researchers face in scientific research, and how do they cope with these challenges?

RQ4. How do researchers perceive the argument that using AI in scientific research constitutes "academic cheating"?

RQ5. How do researchers perceive the impact of ChatGPT on research creativity and efficiency?

RQ6. What are researchers' views on whether AI should be banned or fully adopted if it proves capable of writing research papers better than humans?

METHODOLOGY

Design

This study employed a qualitative research design to explore researchers' perceptions of AI-powered tools, particularly ChatGPT, and their impact on research creativity, efficiency, and scholarly integrity. A cross-sectional survey using a purposive sampling strategy was conducted to capture diverse perspectives across academic levels and disciplinary contexts within education and psychology. The survey instrument, designed specifically for this investigation, comprised six open-ended questions that systematically examined participants' preferences for AI-powered research tools, strategies for overcoming difficulties in interpreting research findings, major challenges encountered in scientific research and corresponding coping mechanisms, ethical perspectives on whether AI use constitutes academic cheating, perceptions of ChatGPT's impact on research creativity and efficiency, and views on whether AI should be banned or fully adopted if proven capable of outperforming human research writing. This open-ended format was deliberately chosen to elicit rich, detailed narratives that quantitative approaches cannot capture, allowing participants to articulate not merely what tools they use or challenges they face, but how they make sense of AI integration, what doubts and adaptations characterize their engagement, what ethical distinctions they draw, and how their perspectives evolve with experience.

The instrument's design was informed by the methodological triangulation strategy underpinning the study, ensuring that the data collected would be amenable to SWOT analysis for strategic assessment, thematic analysis following Braun and Clarke's (2006) six-step framework for identifying deep meaning patterns, and systematic open coding for preserving experiential richness and participant voice. All participants provided online informed consent prior to participation, responses were anonymized at the point of data entry to protect confidentiality, and data were stored securely on password-protected university servers accessible only to the research team, with these ethical protocols ensuring that participants could respond candidly about their AI engagement without concern for identification or professional repercussions.

Participants

The sample was selected using the snowball method, as Moussa and Elnersh (2025) refer, and consists of 112 participants with a variety of academic degrees. Among them, 2 participants hold post-doctoral degrees, while 20 participants have completed a doctorate. A larger group of 26 participants holds a master's degree. Most of the sample, 64 participants, have obtained diplomas [waiting list for registering for Master's]. This distribution reveals a predominance of diploma holders but also includes a fair representation of those with master's and doctoral degrees, though in smaller numbers. The small number of post-doctoral participants reflects the typically smaller population within this academic category. The mix of academic qualifications in the sample allows for a comprehensive exploration of the research topic, capturing a broad spectrum of academic experiences and perspectives. All participants provided online informed consent prior to participation. Responses were anonymized, stored securely, and reported in aggregate to ensure confidentiality.

The sample for this study shows a wide array of academic disciplines within the field of education and psychology. The most prominent major is *Special Education*, which is represented by a significant portion of the participants, showcasing a focus on the needs and development of individuals with disabilities. Another key area is *Educational Psychology*, with several participants specializing in understanding the cognitive and emotional processes in educational settings. Additionally, a notable number of participants are enrolled in *Curriculum and Instructional Methods and Educational Technology*, which covers the design, implementation, and evaluation of educational programs and the integration of technology into teaching practices. Other participants are pursuing majors in *Psychological Health*, which involves the study of mental health and therapeutic interventions, and *Comparative Education, Educational Administration, and Planning*, which examines different educational systems and their management. There is also

Table 1. AI-powered research assistance tools: Categories, frequencies, and examples

Tool Category	n	%	Examples Mentioned	Primary Functions
AI Writing Assistants	89	79.5	ChatGPT, Grammarly, Trinka, Writefull	Text generation, grammar checking, and style improvement
Reference Management	67	59.8	Zotero, Mendeley, EndNote	Citation organization, bibliography generation
Literature Discovery	54	48.2	Elicit, ResearchRabbit, Consensus	Paper search, summarization, relevance screening
Statistical Analysis	48	42.9	IBM SPSS, JASP, Orange	Data analysis, statistical computation, visualization
Visualization Tools	31	27.7	Canva, MindMeister, Lucidchart	Diagram creation, concept mapping, poster design
AI Translation	29	25.9	DeepL, Google Translate	Language translation, multilingual research support
Fact-Checking	19	17.0	Scite, Iris.ai	Source verification, citation context analysis

Note. Total participants N = 112. Percentages sum to more than 100% due to multiple tools mentioned per participant.

representation from diverse fields such as *Human Studies and Sociology* (from Al-Azhar University), and even *Dentistry* and *Pediatric Dentistry*, indicating a wide-ranging academic interest within the sample.

Data Analysis Strategy

This study employed three triangulated qualitative analysis methods, SWOT analysis, thematic analysis following Braun and Clarke's (2006) six-step framework, and systematic open coding, deliberately integrated to capture the multidimensional nature of researchers' experiences with ChatGPT as simultaneously a strategic resource, a source of meaning-making, and a lived reality. The analysis proceeded through five systematic stages.

First, during data preparation and familiarization, all 112 open-ended responses were compiled into a single dataset, anonymized with participant codes (P1-P112), and imported into NVivo 14 qualitative analysis software, where two researchers independently read all responses multiple times to achieve immersion in the data while recording initial observations and reflexive notes.

Second, during open coding, both researchers independently conducted line-by-line coding identifying discrete units of meaning, generating 347 initial codes that were subsequently consolidated through conceptual merging into 47 distinct first-order codes; for example, statements about "using ChatGPT to find articles," "summarizing papers with AI," and "AI for literature scanning" were consolidated under the code "AI-assisted literature review."

Third, during axial coding, the first 47 first-order codes were organized into conceptual categories by identifying relationships between codes and grouping them into higher-order categories, yielding 18 second-order categories such as "AI as research tool," "cognitive impacts," and "ethical concerns."

Fourth, during selective coding and theme development, the 18 categories were synthesized into overarching themes through iterative review, discussion between researchers, and refinement of theme boundaries, following Braun and Clarke's (2006) framework to ensure themes captured core patterns in the data while remaining grounded in participant voices.

Fifth, to ensure analytical rigor, inter-coder reliability was assessed on a random sample of 20% of responses (n = 22), with Cohen's kappa coefficient calculated at $\kappa = 0.84$, indicating strong agreement, and all discrepancies were resolved through consensus discussion before the final coding framework was applied to the full dataset.

Parallel to this coding process, a SWOT analysis framework was systematically applied to categorize findings according to Strengths, Weaknesses, Opportunities, and Threats, with both researchers independently mapping participant responses onto the four SWOT dimensions for each research question and reaching consensus on classification, thereby providing a strategic structure complementary to the thematic analysis. To enhance trustworthiness, the study addressed Lincoln and Guba's (1985) criteria through prolonged engagement with data and peer debriefing between researchers, ensuring credibility, rich thick descriptions of participants and context, enabling transferability, audit trails documenting all analytical decisions, ensuring dependability, and systematic grounding of all themes in participant quotes, establishing confirmability.

Throughout this analytical process, the research team maintained reflexive awareness of how their own perspectives might shape interpretation, documenting assumptions and periodically revisiting raw data to ensure themes remained genuinely grounded in participant experiences rather than imposed by researcher expectations.

RESULTS

Prefer a Specific Type of AI-Powered Research Assistance

The analysis of participants' responses regarding their preferences for AI-powered research assistance tools revealed a diverse and stratified landscape of technological engagement, with 112 participants collectively mentioning 347 instances of AI tool usage across six functional categories. **Table 1** presents the distribution of tool types mentioned, their frequencies, and representative examples.

The distribution of tool preferences reveals that researchers are selectively integrating AI into their workflows in ways that reflect their specific needs, contexts, and levels of expertise. The relationship between AI adoption and research experience is complex rather than linear. A post-doctoral researcher (P87) summarized this difference, stating, "*Novices use AI to do things they can't do; experts use AI to do things they could do, but faster or better. Both are valid, but they're different relationships with technology, and they probably have different developmental effects.*"

This distinction between compensatory use and augmentative use has important implications for research training. A senior researcher (P102) warned: "*The danger isn't that novices use AI, it's that they use it instead of learning. If AI writes your literature review, you haven't learned to synthesize*

Table 2. Strategies for interpreting research findings: Frequencies and representative examples

Strategy Category	n	%	Description
Expert Consultation	87	77.7	Seeking guidance from supervisors, mentors, or peers
Literature Re-engagement	76	67.9	Returning to theoretical frameworks and prior studies
Methodological Reassessment	58	51.8	Reviewing data collection and analytical procedures
AI-Assisted Analysis	52	46.4	Using AI tools for alternative interpretations
Interdisciplinary Expansion	41	36.6	Consulting literature outside the immediate discipline
Iterative Reflection	67	59.8	Repeated re-examination of data and assumptions

Note. Total participants N = 112. Percentages sum to more than 100% because of multiple strategies mentioned per participant.

literature. If AI does your statistics, you haven't learned to reason about data. The tool that enables today's project may prevent tomorrow's independence."

Despite these concerns, participants across experience levels expressed optimism about AI's potential when used thoughtfully. A doctoral candidate (P51) captured this balanced perspective: "*AI is like any powerful tool; it can be used well or poorly. The key is education: teaching researchers not just how to use AI, but how to use it critically, how to recognize its limitations, how to maintain their own capabilities while leveraging its strengths. That's the challenge for our field now.*"

When You Encounter Difficulty in Interpreting Your Research Findings, What Steps Do You Take?

The analysis of participants' approaches to resolving difficulties in interpreting research findings revealed a multi-layered process that integrates traditional academic practices with emerging technological supports. **Table 2** presents the frequency of strategies mentioned by participants, organized by thematic category.

The relationship between traditional and AI-assisted strategies is not one of replacement but of complementarity. A post-doctoral researcher (P95) explained: "*AI didn't replace anything for me. It added something new. I still do everything I used to do: talk to mentors, read literature, think hard, and question my methods. Now I also have AI suggesting possibilities I might have missed. It's an addition, not a substitution.*"

However, participants also expressed concerns about how AI might subtly reshape interpretive practices over time. A doctoral candidate (P40) articulated this concern: "*The danger isn't that I'll stop thinking altogether. It's that I'll stop thinking as deeply, because AI gives me acceptable interpretations without the struggle. I might settle for 'good enough' when better was possible if I'd pushed through the difficulty.*"

The sequencing of strategies emerged as a critical metacognitive skill. A post-doctoral researcher (P88) explained the logic: "*AI after my own thinking expands what I consider; AI before my own thinking replaces it. Expert consultation after AI helps me evaluate what AI suggested; expert consultation before AI would limit what AI could offer. The sequence matters as much as the tools.*"

Despite the increasing availability of AI tools, participants consistently affirmed the social foundation of interpretation. A senior researcher (P101) summarized this enduring priority: "*AI will get better at generating possibilities, at identifying patterns, at suggesting connections. But interpretation -real interpretation, the kind that advances understanding- will always be human. Because interpretation isn't just about what the data says. It's about what matters, what's significant, what advances a conversation. Those are human judgments about human concerns. AI doesn't have skin in that game.*"

What Are the Biggest Challenges You Face in Scientific Research, and How Do You Handle Them?

The analysis of participants' descriptions of research challenges and their corresponding coping strategies revealed a complex landscape of obstacles spanning the entire research process, from literature access to time management. **Table 3** presents the frequency of challenges mentioned by participants, organized by thematic category, along with the strategies employed to address them.

Among participants, 76% described their coping strategies as evolving. A post-doctoral researcher (P70) traced this evolution: "*When AI first appeared, I used it for everything; it was new and exciting. Then I pulled back, worried about dependency. Now I think I've found a balance: AI for some things, traditional methods for others, with conscious decisions about which is which. The balance keeps shifting as I learn.*"

The integration of AI into challenge management was described in carefully bounded terms. A post-doctoral researcher (P82) summarized this balanced perspective: "*AI helps with many of these challenges- finding literature, suggesting analyses, improving writing. But it doesn't eliminate them. You still need to know what you're looking for, understand what the analysis means, and have something to say. AI is a powerful tool, but it's still just a tool. The work of research remains human work.*"

Some Argue That Using Artificial Intelligence in Scientific Research Is Akin to "Academic Cheating." What Is Your Opinion on This?

The question of whether using artificial intelligence in scientific research constitutes academic cheating elicited diverse and thoughtfully reasoned responses from participants, revealing a spectrum of positions that defied simple categorization. **Table 4** presents the distribution of participant perspectives on this ethically charged question.

Notably, 71% of participants expressed views that combined elements from multiple categories. A participant from the "AI as Legitimate Tool" category (P11) acknowledged this nuance: "It's not the tool itself; it's how you use it. If you're just copy-pasting without thinking, that's cheating. But if you're using it to clarify your own ideas, that's no different from talking to a colleague."

This sentiment was echoed by a participant who leaned towards the "Potential Cheating" view (P64): "I think it's cheating if you claim the AI's work as your own without adding your own intellectual contribution. But using it to help you

Table 3. Participant perspectives on AI as academic cheating

Challenge Category	n	%	Description	Primary Coping Strategies
Literature Access	81	72.3	Difficulty obtaining full-text articles, paywall barriers	Alternative platforms (ResearchGate, Academia.edu), interlibrary loan, AI-assisted summarization, colleague networks
Data Collection	67	59.8	Securing adequate samples, instrument design, and participant recruitment	Online survey platforms, snowball sampling, expert consultation, and AI-assisted instrument refinement
Statistical Analysis	58	51.8	Selecting appropriate tests, software proficiency, and result interpretation	Statistician consultation, AI-assisted computation, peer collaboration, online tutorials
Methodological Design	49	43.8	Experimental design, survey construction, sampling strategy	Supervisor guidance, methodology textbooks, AI-generated design alternatives, and pilot studies
Language Barriers	42	37.5	Working with non-native language sources, academic writing in English	AI translation tools, proofreading software, writing centers, and co-author networks
Writing Challenges	71	63.4	Organizing arguments, maintaining clarity, and meeting publication standards	Multiple revisions, peer feedback, AI writing assistance, structured templates
Time Management	64	57.1	Balancing research with teaching, service, and personal responsibilities	Prioritization, structured schedules, AI-automated tasks, boundary setting
Keeping Current	38	33.9	Staying updated with rapidly evolving methodologies and AI tools	Academic social media, journal alerts, conference attendance, peer networks

Note. Total participants N = 112. Percentages sum to more than 100% due to multiple challenges mentioned by participants.

Table 4. Participant perspectives on AI as academic cheating

Perspective Category	n	%	Core Argument
AI as Legitimate Tool	41	36.6	AI is no different from other research tools; cheating depends on use, not the tool.
AI as Potential Cheating	28	25.0	AI becomes cheating when it replaces thinking or when its use is undisclosed.
Context-Dependent View	37	33.0	Cheating depends on how, why, and to what extent AI is used
Unqualified Rejection	6	5.4	Any AI use in research constitutes cheating

Note. Total participants N = 112.

Table 5. Participant perspectives on ChatGPT's impact on creativity and efficiency

Theme	n	%	Core Concept
Theme 1: AI as Cognitive Amplifier	38	33.9	AI extends human cognition, generating possibilities for researcher evaluation.
Theme 2: AI as Cognitive Atrophy	29	25.9	Reliance on AI weakens independent thinking and analytical capacity
Theme 3: Primacy of Use Patterns	41	36.6	Impact depends on user characteristics, task type, and deployment strategy.
Theme 4: Efficiency-Originality Paradox	24	21.4	Tension between AI's conventional efficiency and conditions for genuine originality
Theme 5: Developmental Trajectories	31	27.7	AI's effects evolve as users gain experience and their engagement patterns.

Note. Total participants N = 112. Percentages exceed 100% due to participants expressing views aligned with multiple themes.

articulate your own thoughts better? That's just using a tool." Another participant (P33) added, "The line is blurry. If I use AI to fix my grammar, is that cheating? No. If I use it to generate a full analysis, then yes. The problem is everything in between."

The "Uncertainty Problem" emerged as a widely shared concern. A participant (P98) stated: "*We're all trying to figure out where the boundaries are. It's not clear yet. We need a community conversation, not individual judgment.*" A post-doctoral researcher (P109) articulated this forward-looking view: "*We don't have the answers yet, but that doesn't mean we won't find them. The scholarly community has grappled with new technologies before and developed norms over time. We'll do it again. It's messy now because it's new, but we'll figure it out together.*"

Do You Think Researchers Who Rely on ChatGPT Are More Creative or Less Efficient? And Why?

The question of whether researchers who rely on ChatGPT demonstrate greater creativity or reduced efficiency elicited polarized yet thoughtfully nuanced responses, revealing five distinct thematic patterns in how participants conceptualize AI's role in scholarly work. **Table 5** presents the distribution of these themes across the participant sample.

Theme 1: AI as Cognitive Amplifier. A doctoral student (P12) described this perspective: "*It's like having a brainstorming partner who never gets tired. I throw ideas at it, it throws back possibilities, and that sparks my own thinking. I'm more creative because I'm considering things I wouldn't have thought of on my own.*"

Theme 2: AI as Cognitive Atrophy. A senior researcher (P99) expressed the opposing concern: "*The struggle is where*

Table 6. Participant perspectives on banning versus adopting AI in research writing

Perspective Category	n	%	Core Rationale
Conditional Adoption	48	42.9	Adopt with clear guidelines, human oversight, and ethical frameworks
Unqualified Adoption	31	27.7	Embrace AI's capabilities while redirecting human effort to higher-order tasks.
Qualified Opposition	22	19.6	Resist full adoption; preserve human role in core scholarly functions
Unqualified Ban	11	9.8	Prohibit AI entirely, regardless of capability
Total	112	100	

Note. Total participants N = 112.

learning happens. If AI removes the struggle, it removes the learning. You get efficiency today, but you lose the capacity to think independently tomorrow."

Theme 3: The Primacy of Use Patterns. A participant (P45) stated: "*It's not about the tool. It's about the user. The same ChatGPT that helps one researcher think more deeply could make another researcher lazy. It depends on what you bring to it.*"

Theme 4: The Efficiency-Originality Paradox. A participant (P103) explained: "*AI is efficient because it produces conventional, predictable content quickly. But that's the opposite of what you need for breakthrough thinking. Breakthroughs come from inefficiency- from struggle, from detours. I worry AI will give us more papers but fewer ideas.*"

Theme 5: Developmental Trajectories. A participant (P15) described their own evolution: "*When I first started using it, I used it for everything. Then I realized I was relying on it too much, so I pulled back. Now I have a better sense of when it's useful and when I need to do the work myself. It's a learning process.*"

If Future Research Shows That Artificial Intelligence Can Write Research Papers Better Than Humans, Would You Support Banning It or Fully Adopting It?

The question of whether artificial intelligence should be banned or fully adopted if proven capable of writing research papers better than humans elicited responses that revealed fundamental assumptions about the nature of scholarship, the value of human intellectual contribution, and the appropriate relationship between researchers and their tools. **Table 6** presents the distribution of participant perspectives on this forward-looking question.

The "boundary problem" emerged as a central concern. A participant (P71) articulated this difficulty: "*Where do you draw the line? If AI writes the whole paper, is the researcher still the author? If the researcher only did the thinking and AI did the writing, is that different from dictating to a human assistant? These are not simple questions.*"

A participant (P77) explained their "*Conditional Adoption" stance: "We can't ban it; that's unrealistic. But we can't just adopt it without thinking, either. We need guidelines, transparency requirements, and ways to acknowledge AI contributions. The goal should be to use it in ways that enhance scholarship, not replace it.*"

The "Unqualified Adoption" view was explained by a participant (P29): "*If AI can write better papers, why would we not use it? That's like refusing to use a calculator because it does math better than you. Let AI do the writing, and let humans focus on what really matters: asking the right questions, designing the right studies, thinking deeply about what the answers mean.*"

A participant (P53) expressed the "Qualified Opposition" view: "*The purpose of research isn't just to produce papers. It's to learn and to think. If we let AI think, we lose what makes scholarship meaningful. Efficiency isn't everything. Sometimes the struggle is the point.*"

Notably, 73% of participants across all categories called for collective deliberation. A post-doctoral researcher (P91) articulated this sentiment: "*I don't want to decide alone whether AI use is okay. If I'm the only one using it heavily, I look like I'm cheating. If I'm the only one not using it, I look inefficient. We need to decide together what kind of scholarship we want.*"

DISCUSSION

The findings of this study contribute to the expanding literature on artificial intelligence in academic research, providing empirical grounding for what has been largely a theoretical debate. By merging SWOT analysis, thematic analysis, and systematic coding of participant responses, this investigation delivers a nuanced account of how researchers perceive, experience, and navigate the benefits and challenges of AI-assisted scholarship. The results both validate existing research and extend it in new directions, while also highlighting tensions and complexities that merit ongoing scrutiny from the academic community.

The finding that 79.5% of participants reported using AI writing assistants, with ChatGPT mentioned most frequently, aligns with recent surveys that document the rapid adoption of generative AI in academic contexts (Hosseini et al., 2023; Strzelecki, 2024). However, the present study extends this descriptive finding by elucidating the qualitative texture of adoption patterns, the portfolio strategies through which researchers assemble personalized collections of tools for diverse tasks, the developmental trajectories along which usage patterns evolve, and the metacognitive frameworks researchers employ to regulate their engagement with AI. This suggests that adoption is not a simple binary but a complex process of sensemaking that unfolds differently across individuals and contexts.

The persistence of expert consultation as the most cited interpretive strategy (77.7%), even among heavy AI users, challenges narratives that position AI as supplanting human judgment in scholarly work. This finding aligns with Lee et al. (2024), who noted that AI-assisted thematic analysis still required significant human oversight for credible results, and with Van Dis et al. (2023), who contended that AI should act as collaborator, not author, in scientific writing. Extending these insights, the present study clarifies *why* human consultation is prized: for contextual judgment, disciplinary expertise, and interpersonal engagement—qualities AI lacks. Participants regarded expert consultation as qualitatively distinct from AI interaction, not simply more reliable but uniquely valuable,

offering understanding, dialogue, and connection instead of information, output, or transaction.

The distinction between generative and evaluative functions, maintained by 89% of AI-using participants, provides empirical support for theoretical frameworks that position AI as a tool for expanding possibilities while reserving judgment for humans (Farrokhnia et al., 2023; Rahman & Watanobe, 2023). This finding suggests that researchers are developing sophisticated mental models of AI's capabilities and limitations, treating it as a source of raw material for their own thinking rather than as an authoritative interpreter. This distinction is consistent across experience levels, tool types, and research tasks, suggesting it is a foundational principle for responsible AI integration—one that should inform training programs and institutional guidelines.

A paradox emerges from the experiences of 21.4% of participants: the very efficiency that makes AI appealing may undermine the conditions for genuine originality. This tension resonates with broader critiques of AI's potential to homogenize scholarly output (Bender et al., 2021; Birhane et al., 2022). Participants observed that what enables AI to generate conventional, predictable content quickly is precisely what renders it inimical to the slow, uncertain labor from which originality springs. In doing so, this finding grounds theoretical critiques in researchers' lived experience, revealing that practitioners are already grappling with the trade-off between productivity and innovation. The implication is not that AI should be abandoned, but that its integration must be accompanied by intentional cultivation of the slow, inefficient, uncertain work that originality demands.

The developmental trajectories of 27.7% of participants—shifting from initial enthusiasm to more measured use—reveal that researchers' relationships with AI evolve through experience. This finding echoes technology adoption literature, which holds that meaningful integration requires time and reflection (Davis, 1989; Venkatesh et al., 2003), yet extends it, exposing the specific contours of this evolution in academic contexts. The transition from comprehensive to selective use, from trust to skepticism to calibrated trust, and from tool-focused to task-focused engagement charts a learning curve institutions can scaffold rather than leave to individual trial and error. Together, this pattern signals a clear opportunity for institutional support.

The experience gradient in AI use—novices employing tools compensatorily, experts augmentatively—entails profound implications for research training. This finding supports broader expertise-development research, which emphasizes that effective tool use depends on foundational capability (Ericsson & Pool, 2016; Dreyfus & Dreyfus, 1986). In the AI context, however, it exposes a critical concern: the tools themselves may obstruct novices from developing the very capabilities they need. When AI takes over literature synthesis, statistical analysis, or writing for novice researchers, those researchers risk never acquiring the deep understanding cultivated through independently wrestling with these activities. This paradox—tools designed to enable may inadvertently disable—demands that training programs intentionally structure learning to scaffold, not supplant it.

The boundary problem is the difficulty of specifying where to draw boundaries between acceptable and unacceptable AI use, which emerged as a central concern across all research questions. This finding aligns with broader scholarly discourse about the need for ethical guidelines (Floridi & Chiriatti, 2020; Sallam, 2023), but reveals that the challenge is not merely the absence of rules but the inherent difficulty of making distinctions in contexts where the same AI use might be appropriate in one situation and problematic in another. Participants' calls for principle-based rather than rule-based guidance resonate with recent proposals for adaptive governance of AI in academia (Whittlestone & Clark, 2021; Stahl et al., 2023), suggesting that institutions should focus on developing researchers' capacity for ethical judgment rather than attempting to anticipate every possible scenario.

The finding that 68% of participants expressed views aligned with multiple thematic categories across research questions challenges simplistic characterizations of researchers as either pro- or anti-AI. This conceptual complexity reflects the genuinely multidimensional nature of AI integration, which involves trade-offs between competing values, efficiency versus depth, assistance versus substitution, convention versus originality, and access versus equity. Researchers are not taking sides in a binary debate but forming nuanced, context-sensitive positions that acknowledge both benefits and risks. This finding suggests that scholarly discourse about AI should resist polarization and instead cultivate the kind of complexity that participants themselves demonstrated.

The equity concerns raised by 64% of participants, about differential access to tools, training, and support, echo broader critiques of technology's potential to exacerbate existing inequalities (Noble & Smith, 2018; Benjamin, 2019). In the research context, these concerns are particularly acute because AI tools could either democratize scholarship by providing powerful resources to researchers at under-resourced institutions or create new divides between those who know how to leverage AI effectively and those who do not. The finding that participants from less-resourced institutions reported greater reliance on AI for tasks they could not otherwise perform, combined with concerns about whether such use supports genuine capability development, suggests that equity must be a central consideration in AI integration efforts.

Continued apprehensions about academic integrity across all research questions, with 71.4% of participants raising ethical considerations in some form, align with the extensive literature on AI and academic dishonesty (Cotton et al., 2023; Perkins, 2023). However, the present study reveals that researchers' ethical reasoning is more nuanced than simple concerns about cheating. Participants distinguished between using AI to enhance versus replace thinking, between disclosed and undisclosed use, and between different purposes and contexts. This suggests that ethical guidelines should engage with this complexity rather than imposing blanket prohibitions that researchers would likely ignore or resent.

Across all participant categories, 73% called for collective deliberation on AI norms—a clear recognition that the academic community needs shared analysis. This aligns with sociological perspectives on technology adoption, which hold

that norms emerge through collective negotiation, not individual decision-making (Bijker, 2001; Pinch & Bijker, 1984). Institutions can respond by creating structured opportunities for researchers to discuss AI use, exchange experiences, and develop shared practices. Such forums serve a dual purpose: helping researchers learn from one another while building the collective understanding from which shared standards grow.

CONCLUSION

The present study's findings both align with and extend existing theoretical frameworks for understanding technology adoption in academic contexts. The technology acceptance model (Davis, 1989) emphasizes perceived usefulness and perceived ease of use as predictors of adoption. While these factors were certainly relevant, participants adopted tools they found useful and usable. The present study reveals additional dimensions that shape adoption patterns: perceived impact on cognitive development, alignment with disciplinary values, consistency with ethical commitments, and effects on scholarly identity. These findings suggest that existing technology acceptance models, developed primarily in organizational contexts, may need adaptation to capture the distinctive values and concerns of academic work.

Similarly, the findings extend recent theoretical work on AI ethics in academia. Floridi and Chiriatti (2020) proposed principles of transparency, accountability, and beneficence for AI use. The present study reveals how researchers operationalize these principles in practice, through disclosure practices, through maintaining human oversight, and through calibrating trust based on experience. Sallam (2023) called for ethical guidelines for AI in healthcare education and research; the present study provides empirical grounding for such guidelines by revealing the specific concerns and practices of researchers themselves.

The study also contributes to methodological debates about how to study AI in academic contexts. The triangulation of SWOT analysis, thematic analysis, and systematic coding proved valuable for exploring various aspects of the phenomenon: strategic, semantic, and experiential. This approach could usefully be applied in future research examining other aspects of AI integration, or in comparative studies across disciplines, institutions, or national contexts. The finding that different analytical lenses revealed different but complementary insights suggests that methodological pluralism is particularly valuable for studying complex, multidimensional phenomena like AI integration.

LIMITATIONS

Several limitations of this study warrant consideration when interpreting its findings. First, the sample, while diverse in academic level and disciplinary background, was predominantly drawn from education and psychology (82.1%). Research practices, methodological norms, and appropriate roles for AI may differ substantially in other fields, natural sciences, engineering, humanities, and professional programs, limiting the transferability of findings to those contexts. Future research should examine discipline-specific patterns and variations, exploring whether the themes identified here manifest differently across fields with different epistemic cultures.

Second, the predominance of diploma holders (57.1%) means the findings may disproportionately reflect the perspectives of early-career researchers. While this group is important, they represent the next generation of scholars and are actively forming their research identities; their views and practices may differ from those of highly experienced researchers. The experience gradient identified in the findings suggests that career stage significantly shapes AI engagement, but the sample's composition limits robust comparison across stages. Future research with more balanced sampling across career stages could illuminate developmental trajectories more fully.

Third, the study relied on self-reported data, which is subject to social desirability bias, recall limitations, and discrepancies between reported and actual practices. Participants may present themselves as more ethically reflective or more critically engaged than they are, or may not accurately remember their AI use patterns. Future research should complement self-reports with behavioral data, analysis of writing processes, tracking of tool use, and experimental comparisons of AI-assisted and non-AI-assisted outputs to triangulate findings and assess alignment between reported perceptions and actual practices.

Fourth, the cross-sectional design captures perceptions at a single point in time but cannot track how these perceptions evolve as AI technologies develop and as users gain experience. The developmental trajectories participants described suggest that relationships with AI change significantly over time, but this study could only capture retrospective accounts of such change. Longitudinal studies following researchers over months or years would illuminate how AI engagement patterns evolve and how initial enthusiasm may (or may not) translate into sustained, beneficial use.

Fifth, the study did not employ a systematic comparison between AI-assisted and human-only analytical processes. While participants reported their perceptions of AI's effects on their thinking and work, the study cannot directly assess whether AI use improves or diminishes research quality, originality, or efficiency. Experimental designs comparing outputs produced with and without AI assistance or tracking changes in researcher capabilities over time with different levels of AI engagement would strengthen causal claims about AI's effects.

Sixth, the snowball sampling method may have introduced selection bias, as participants likely recruited others with similar interests and perspectives. This could have amplified certain viewpoints while underrepresenting others. The diversity of perspectives obtained, ranging from unqualified rejection to unqualified adoption, suggests that the sample captured meaningful variation, but the possibility of bias cannot be eliminated.

Finally, as with all qualitative research, the analytical process involves interpretation. While rigor was enhanced

through inter-coder reliability assessment, audit trails, and member checking, different researchers might have identified different themes or emphasized different aspects of the data. The findings represent one plausible interpretation, grounded systematically in the data, but not the only possible interpretation.

IMPLICATIONS

Despite these limitations, the study offers several contributions that warrant cautious generalization. The finding that AI's impact depends more on use patterns than on the technology itself, on who uses it, how, for what purposes, and with what awareness, suggests that efforts to shape AI integration should focus on researcher development rather than tool regulation. The experience gradient, the sequencing strategies, and the generative-evaluative distinction all point to learnable practices that could be taught. This shifts the policy conversation from "should AI be allowed?" to "how can we help researchers use AI wisely?"

The finding that researchers across perspectives value human connection, expert consultation, collaborative dialogue, and scholarly community suggests that investments in AI should complement rather than compete with investments in the social infrastructure of research. AI may make certain tasks more efficient, but it cannot replace the judgment that emerges from sustained engagement with a scholarly community. This implies that institutions should resist the temptation to see AI as a cost-saving measure that can replace human mentorship or collaboration, and instead view it as a tool that, used well, can enhance the distinctly human work of scholarship.

The widespread ambivalence and uncertainty expressed by participants, the boundary problem, concerns about hidden costs, and the difficulty of specifying rules suggest that the academic community is in a period of transition, aware that fundamental questions need answering but uncertain about how to answer them. This calls for humility in institutional responses: rather than imposing premature solutions, institutions might better serve their communities by creating spaces for collective sensemaking, supporting experimentation and reflection, and cultivating the ethical and critical capacities that will serve researchers regardless of how AI technologies evolve.

The study ultimately affirms that scholarship remains fundamentally human work. AI can assist with many tasks, finding literature, suggesting analyses, improving writing, but it cannot make the judgments that matter most: what questions are worth asking, what evidence is sufficient, what arguments are convincing, what contributions advance a field. These judgments require the kind of understanding that comes from immersion in a scholarly community, from struggling with difficult problems, from caring about getting it right. AI, as one participant noted, "doesn't have skin in that game." The task for the academic community is not to decide whether AI belongs in research—it already does—but to ensure that its integration serves rather than subverts the fundamentally human purposes that scholarship exists to advance.

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AI statement: The authors stated that ChatGPT was used in an assistive capacity during manuscript preparation, limited to language refinement and formatting. All substantive intellectual content—including conceptual framing, data analysis, interpretation, and argumentation—represents the original work of the authors, who assume full responsibility for the published manuscript.

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