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Ethical Challenges in the Era of Generative AI: Insights from a Practice-Informed Rapid Review

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ABSTRACT

This study investigates the integration of Generative AI (GenAI) into academic research, highlighting both its transformative potential and the ethical, methodological, and epistemological challenges it introduces. While GenAI enhances efficiency in tasks like text generation, data analysis, and translation, it raises serious concerns around authorship, originality, transparency, data privacy, and accountability. Through a rapid review of literature from 2022 to 2025, guided by the European Code of Conduct for Research Integrity, the study identifies recurring risks such as algorithmic bias, fabricated citations, and diminished scholarly authorship. In response, it proposes a five-principle ethical framework—human oversight, accuracy, accountability, data protection, and institutional governance—and emphasizes that responsible GenAI use requires not only technical safeguards but also ethical literacy, critical reflection, and transparent disclosure. Ultimately, GenAI should serve as a collaborative partner that augments human creativity while preserving the integrity and rigor of scientific inquiry.

Keywords: Generative Artificial Intelligence, research ethics, academic integrity, accountability, transparency, data privacy

INTRODUCTION

The rapid advancement of Generative Artificial Intelligence (GenAI) has profoundly reshaped academic research by enabling the creation of realistic text, images, and even synthetic datasets. These technologies promise to accelerate knowledge production, enhance accessibility, and improve the efficiency of research workflows. However, their integration into scholarly practice also raises serious ethical, methodological, and epistemological questions concerning authorship, originality, data integrity, and accountability (European Commission Directorate General for Research and Innovation, 2024).

Recent evidence underscores the urgency of this issue. Nearly 1% of abstracts submitted to the preprint repository arXiv in 2023 displayed indicators of GenAI-generated content (Gray, 2024), suggesting that these tools are rapidly becoming embedded within the academic ecosystem. As GenAI's sophistication increases—capable even of conducting research with minimal human input (Sakana.ai, 2024)—its potential to disrupt traditional research norms and ethical standards becomes increasingly apparent (Kobak et al., 2024; Liang et al., 2024).

A clear distinction must therefore be drawn between Artificial Intelligence (AI) and Generative Artificial Intelligence (GenAI), as their roles and ethical implications differ significantly. According to the European Commission (2018, p. 4), AI systems demonstrate "intelligent behaviour by analysing their environment and taking actions—with some degree of autonomy—to achieve specific goals." In contrast, GenAI systems "generate new content in response to prompts based on their training data" (Lorenz et al., 2023, p. 8). This distinction is crucial, as GenAI's capacity to autonomously produce seemingly original text and data raises unique challenges in research authorship, reproducibility, and moral accountability.

Despite GenAI's transformative potential, research on its ethical dimensions remains fragmented and underdeveloped. The majority of existing scholarship focuses on academic integrity issues among students, such as plagiarism and inappropriate AI-assisted writing (Cotton et al., 2024; Foltýnek et al., 2023; Perkins, 2023). However, ethical implications for research practices—including data analysis, publication, peer review, and intellectual property—have received limited attention. Key challenges include the difficulty of replicating results due to stochastic outputs (Perkins & Roe, 2024c) and the lack of transparency in how these systems generate responses (Weber-Wulff et al., 2023).

Conceptual analyses have identified several recurring ethical risks, including algorithmic bias, inaccuracy, the "black box" problem, and the absence of moral agency in AI-driven processes (Resnik & Hosseini, 2024). To mitigate these concerns, Kurz and Weber-Wulff (2023) propose three core principles for responsible AI use: it must be *permitted*, *transparent*, and *accompanied by full accountability* on the part of the user.

In response to these challenges, international organizations and regulatory bodies have begun developing ethical frameworks to guide AI integration in research. UNESCO (2024) and Miao and Holmes (2023) emphasize the potential for GenAI to enhance research productivity and inclusivity while warning of emerging risks related to fairness, bias, and data misuse. Similarly, various academic publishers have released AI-use policies, though many have been criticized for being overly restrictive or inconsistently implemented across disciplines (Perkins & Roe, 2024a).

Against this backdrop, the present study aims to explore the ethical implications of GenAI integration in academic research and to identify strategies for ensuring its responsible use. Specifically, it seeks to address two guiding research questions:

What ethical challenges emerge from the use of Generative AI across different stages of the research process—from conceptualization to dissemination?

How can researchers and institutions ensure the responsible and transparent integration of GenAI tools while upholding the principles of research integrity and academic freedom?

By examining GenAI applications throughout the research lifecycle, this study identifies key ethical concerns—including data privacy, accuracy of outputs, bias, transparency, intellectual property rights, and research misconduct—and proposes practical recommendations to support ethical, transparent, and accountable GenAI use in academic contexts.

LITERATURE REVIEW

The ethical integration of Generative Artificial Intelligence (GenAI) in academic research represents a critical yet underexplored area within contemporary scholarship. While the potential benefits of GenAI are widely recognized—such as increased efficiency, accessibility, and automation—the ethical, social, and epistemological implications of its adoption remain poorly understood.

Conceptualizing Artificial Intelligence and Generative AI

The distinction between AI and GenAI is foundational to understanding their ethical implications. Artificial Intelligence (AI) refers to computational systems that analyze data and perform decision-making tasks with some degree of autonomy (European Commission, 2018). Generative AI (GenAI), by contrast, is a subclass of AI that creates new content in response to prompts based on patterns learned from large datasets (Lorenz et al., 2023). Whereas traditional AI supports analysis and prediction, GenAI participates directly in the creation of research materials, including text, images, code, and simulated data—thus introducing profound challenges concerning authorship, originality, and reproducibility.

Emerging Ethical Concerns in Research Practice

The application of GenAI in academic research raises multifaceted ethical concerns. These include transparency of tool operation, potential biases embedded in training data, reliability of generated outputs, and the risk of inadvertent plagiarism. Resnik and Hosseini (2024) emphasize that GenAI tools lack moral agency, meaning that accountability must rest entirely with the human researcher. Moreover, the "black box" nature of many GenAI systems—wherein internal decision-making processes are opaque—creates difficulties in verifying or reproducing results, challenging the foundational principle of scientific transparency (Weber-Wulff et al., 2023).

Current Research Gaps and Disciplinary Contexts

While numerous studies have examined AI use in education, most have centered on academic integrity issues among students (Cotton et al., 2024; Foltýnek et al., 2023; Perkins, 2023). In contrast, research ethics and scientific integrity in GenAI-assisted scholarship have been comparatively neglected. Nonetheless, several domain-specific inquiries have begun to emerge: in psychology (Chenneville et al., 2024), scholars debate the ethical implications of AI-mediated data analysis; in health research, concerns center on privacy and consent (Spector-Bagdady, 2023); and in software engineering, questions arise about authorship and code licensing (Kirova et al., 2023). Despite these contributions, a systematic, cross-disciplinary framework for addressing GenAI ethics in research is still lacking.

Ethical Frameworks and Regulatory Responses

Global and institutional efforts to guide GenAI integration are growing. UNESCO (2024) and Miao and Holmes (2023) advocate for ethical frameworks emphasizing transparency, accountability, and human oversight. Similarly, Kurz and Weber-Wulff (2023) propose that AI use in research should be *permitted* by ethical guidelines, *transparent* in disclosure, and *accountable* through explicit authorship responsibility. However, many journal-level and funding-agency policies remain inconsistent, creating confusion regarding acceptable AI-assisted practices (Perkins & Roe, 2024a).

Theoretical Synthesis and Research Need

Synthesizing across existing literature, several ethical themes consistently emerge:

Transparency and explainability in AI outputs.

Bias and fairness in training data and model use.

Intellectual property and authorship concerns.

Data privacy and informed consent.

Accountability and moral responsibility in automated research.

These recurring issues highlight the urgent need for empirically grounded research to map ethical challenges across the entire research lifecycle. This study therefore aims to address this gap by systematically analyzing how GenAI affects each phase of academic research and proposing actionable guidelines for ethical implementation.

METHODOLOGY

Research Design and Rationale

The ethics of Generative AI (GenAI) in research remain largely underexplored despite its rapid uptake across academic disciplines. Given the fast-paced evolution of GenAI tools, a comprehensive evaluation of each tool would be impractical and quickly outdated. Therefore, this study employs a practice-informed rapid review approach, strategically focusing on representative tools used at different stages of the research process.

This approach enables the researchers to chart the ethical concerns that emerge as GenAI becomes embedded in academic workflows, rather than attempting a full systematic assessment. The study is guided by the European Code of Conduct for Research Integrity (ALLEA, 2023) and informed by the interdisciplinary expertise of the research team, which spans history, computer science, ethics, linguistics, and medicine.

Data Sources and Evidence Base

To build a robust evidence foundation, the study draws upon both peer-reviewed and grey literature published since 2022, complemented by hands-on probes of contemporary GenAI services. Because ethical issues vary across the research life cycle, the distribution of evidence also differs—being more extensive in areas such as text generation, but sparse in later stages like data analysis or visualization.

Where literature was plentiful, we synthesized existing studies and cited them directly. In domains with limited prior research, new empirical probes were conducted to generate illustrative case examples. This blended method balances comprehensiveness with timeliness, ensuring that findings remain relevant to rapidly evolving technologies.

Analytical Framework and Case Study Approach

The study's analytical design employs detailed case reports derived from real-world applications of GenAI tools across multiple research phases. Each case was systematically examined by:

- Comparing GenAI-supported outcomes with conventional research methods,
- Identifying ethical and methodological challenges, and
- Evaluating implications for research integrity.

Rather than attempting an exhaustive tool catalogue, the focus remains on representative cases that highlight recurring ethical patterns. This enables deeper insight into core ethical principles—authorship, transparency, reproducibility, and accountability—across diverse research contexts.

Research Lifecycle Framework

The methodological framework encompasses the entire research lifecycle, structured into four key phases:

a. Conceptualization and Design

This phase involves idea generation, hypothesis formation, and literature review. GenAI tools may assist with multilingual research synthesis, grant proposal drafting, and ethics application writing. These activities raise questions about originality, bias in source selection, and authorship attribution.

b. Data Collection and Analysis

GenAI supports data-driven processes such as transcription, coding, statistical analysis, and even programming/debugging in computational studies. It also assists in generating images or visual data representations, each introducing specific ethical risks related to accuracy, bias, and data provenance.

c. Writing and Communication

GenAI tools are widely used for text generation, paraphrasing, and editing—particularly beneficial for researchers who are English-as-a-Foreign-Language (EFL) users. They enhance linguistic clarity and visual presentation but also raise concerns about intellectual ownership, plagiarism, and the erosion of academic voice.

d. Dissemination and Review

In the final stage, GenAI tools can assist with peer review preparation, publication, and outreach. This introduces issues surrounding transparency in AI-aided content creation, disclosure requirements, and maintaining integrity in public communication of research findings.

Evaluation and Ethical Integration

By examining GenAI tools within their research contexts and comparing outcomes with established integrity standards, this methodology highlights both opportunities and risks. The study prioritizes ethical reflection over technical evaluation, aiming to develop practical recommendations that uphold the principles of transparency, accountability, and research quality.

This approach acknowledges that research activities often occur concurrently rather than sequentially, creating complex ethical intersections that require continuous, context-sensitive evaluation.

RESULTS

Literature Gathering and Summarization

Table 1. Ethical Issues Related To Literature Review

Theme	**Representative Tools**	**Key Findings / Observations**	**Ethical Issues Identified**	**Recommendations / Mitigation Strategies**
Literature Gathering	Perplexity, ResearchRabbit, Consensus, Elicit, Litmap	Tools return mixed-quality results; often include non-academic or predatory sources; may fabricate citations or misunderstand multi-word terms.	Inaccuracy, fabricated references, lack of ransparency, misleading citations.	Verify sources and DOIs manually; cross-check with academic databases; prefer tools linking directly to verified references.
Textual Understanding & Summarization	Enago Read, SciSummary, Scholarcy, NotebookLM, ChatPDF, ChatGPT	Capable of concise summaries but prone to errors, author hallucinations, and colloquial tone; accuracy depends on information position in text.	Hallucinations, superficial understanding, loss of context.	Use for preliminary overviews only; manually verify key claims; pair summaries with human critical evaluation.
Copyright and IP Concerns	All above tools	Users may inadvertently transfer intellectual property rights when uploading copyrighted content.	Violation of copyright laws; unclear data use by providers.	Avoid uploading paywalled papers; read Terms of Service; use platforms without IP transfer clauses.

Table 1 reveals that while Generative AI (GenAI) tools significantly enhance efficiency in literature gathering and summarization, they also present notable ethical and reliability concerns. AI-based platforms such as Perplexity, ResearchRabbit, Consensus, Elicit, and Litmap streamline access to academic sources but frequently return mixed-quality results, including non-academic or predatory materials, fabricated citations, and misinterpreted search terms (Foltýnek et al., 2020). Similarly, summarization tools such as Enago Read, SciSummary, Scholarcy, NotebookLM, ChatPDF, and ChatGPT offer concise overviews but often produce hallucinated content, superficial interpretations, and colloquial tones inconsistent with academic discourse (Liu et al., 2023; Fong & Wilhite, 2017). Ethical issues extend to intellectual property (IP) management, as many GenAI services require users to upload copyrighted texts, thereby risking unauthorized data sharing or implicit transfer of content ownership (Bakos et al., 2014; Steinfeld, 2016). To ensure integrity and compliance, researchers should manually verify AI-generated references, cross-check results with established databases, and avoid uploading paywalled or copyrighted materials. Overall, while GenAI offers clear benefits in research productivity and accessibility, responsible use requires critical human oversight, transparency, and adherence to ethical standards to prevent misinformation, bias, and IP violations (ALLEA, 2023; Perkins & Roe, 2024; Weber-Wulff et al., 2023).

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Study Design and Data Collection

Table 2. Ethical Issues Related To Study Design And Data Collection

Theme	Representative Tools	Key Findings / Observations	Ethical Issues Identified	Recommendations / Mitigation Strategies
Ethical Risk Identification	ChatGPT, Claude, Gemini	GenAI can identify potential ethical issues but lacks contextual moral reasoning.	Overgeneralisation, bias, lack of transparency in ethical judgments.	Maintain human-led ethics reviews; use AI output as advisory, not authoritative.
Survey and Interview Design	ChatGPT, Elicit, Copilot	Useful for generating questions but risks producing biased or culturally insensitive content.	Reinforcement of stereotypes; bias in phrasing; harm to participants.	Pilot test AI-generated questions; review for inclusivity; retain researcher oversight.
Informed Consent	ChatGPT, Claude	Can help draft plain-language consent text but prone to hallucination.	Inaccurate statements, misleading information.	Always apply human validation; avoid full automation of consent documents.

The findings summarized in Table 2 illustrate how Generative AI (GenAI) tools are increasingly applied during the study design and data collection phases of research, providing new efficiencies while introducing notable ethical challenges. In the area of ethical risk identification, tools such as ChatGPT, Claude, and Gemini demonstrate the ability to flag potential ethical concerns but lack the depth of contextual or moral reasoning necessary for complex judgment (Perni et al., 2023). This limitation results in risks of overgeneralization, bias, and insufficient transparency in ethical evaluations (European Commission, 2018). Therefore, GenAI output should be regarded as advisory rather than authoritative, ensuring that human-led ethics reviews remain central to research governance (ALLEA, 2023).

For survey and interview design, GenAI systems like ChatGPT, Elicit, and Copilot are effective in rapidly generating question sets and identifying thematic gaps. However, these systems may inadvertently reinforce stereotypes, use culturally insensitive phrasing, or introduce biases that could harm participants (Currie et al., 2023). Ethical best practice involves pilot testing AI-generated questions, reviewing them for inclusivity, and maintaining researcher oversight to uphold fairness and contextual sensitivity (Council for International Organizations of Medical Sciences, 2016).

Finally, in the area of informed consent, GenAI tools such as ChatGPT and Claude can assist in producing plain-language consent forms that enhance participant comprehension. Nonetheless, these tools are prone to hallucinations and inaccuracies, sometimes generating misleading or incomplete statements (Shiraishi et al., 2024). To protect participant autonomy and data integrity, researchers must validate all AI-generated consent documents manually and avoid full automation of ethical communication.

In summary, while GenAI tools offer valuable support in identifying ethical risks, developing research instruments, and drafting consent materials, their use must remain subordinate to human expertise and ethical judgment. Proper oversight, transparency, and validation processes are essential to ensure that AI-assisted study design aligns with principles of research integrity, participant protection, and cultural sensitivity (Weber-Wulff et al., 2023; Perkins & Roe, 2024).

Transcription and Data Processing

Table 3. Ethical Issues Related To Transcription And Data Processing

Theme	Representative Tools	Key Findings / Observations	Ethical Issues Identified	Recommendations / Mitigation Strategies
Audio/Video Transcription	Zoom, MS Teams, Otter.ai	Efficient but may misrecognize non-native or minority speech patterns.	Data privacy violations; demographic bias; training reuse of recordings.	Use local/offline transcription; anonymize data; seek informed consent for storage/use.
Data Processing	ChatGPT, Copilot, Code Interpreter	Can automate cleaning, imputation, or feature extraction but may introduce errors.	Methodological inconsistency; data fabrication if undocumented.	Log all AI-assisted steps; validate outputs with statistical checks; disclose AI use.
Data Anonymisation	Textwash, LLM-based tools	Effective for structured data; less reliable for text with contextual identifiers.	Re-identification risk; data misuse by third parties.	Combine AI with human review; avoid online tools for sensitive data; ensure compliance with privacy law.

The findings in Table 3 demonstrate that while Generative AI (GenAI) and related technologies greatly improve the efficiency of transcription and data processing, they introduce several ethical and methodological risks that require careful oversight. In audio and video transcription, tools such as Zoom, Microsoft Teams, and Otter.ai enable rapid conversion of speech to text but often misrecognize non-native or minority speech patterns, leading to potential demographic bias and inaccuracies in recorded data (Blodgett & O'Connor, 2017). Additionally, the use of cloud-based transcription services raises data privacy and consent concerns, particularly regarding the storage or reuse of recordings for AI model training (Council for International Organizations of Medical Sciences, 2016). To address these challenges, researchers should prioritize local transcription solutions, ensure explicit participant consent, and adhere to institutional data protection protocols.

In the area of data processing, AI systems such as ChatGPT, Copilot, and Code Interpreter can automate tasks like data cleaning, imputation, and feature extraction, thereby reducing researcher workload. However, these benefits come with the risk of methodological inconsistency and potential data fabrication if outputs are not thoroughly documented (Perkins & Roe, 2024). Since GenAI systems operate stochastically, the same prompt may yield varying outputs, threatening replicability and research transparency (Weber-Wulff et al., 2023). Consequently, it is essential that researchers maintain detailed records of AI-assisted procedures and validate all processed data against recognized standards.

Finally, in data anonymisation, tools like Textwash and other LLM-based systems are useful for structured datasets but remain unreliable for text containing contextual identifiers, where re-identification risks persist (Patsakis & Lykousas, 2023). The potential for data misuse by third parties further complicates ethical compliance, particularly when sensitive information is transmitted to external servers. Researchers should therefore favor institutional or offline anonymisation systems and avoid web-based tools that claim ownership or reuse rights over uploaded data.

Data Analysis and Visualization

Table 4. Ethical Issues Related to Data Analysis and Visualization

Theme	Representative Tools	Key Findings / Observations	Ethical Issues Identified	Recommendations / Mitigation Strategies
Qualitative Analysis	Claude 3 Opus, ChatGPT	Can generate codes and themes but also fabricate supporting quotes.	Data fabrication; hallucination; lack of traceability.	Require evidence-backed coding; human validation of quotes; disclose AI involvement.
Quantitative Analysis	ChatGPT (Python plugin), Copilot	Performs statistical tasks rapidly but may enable "p-hacking."	Reproducibility issues; bias amplification; data manipulation.	Pre-register analysis plans; confirm results manually; emphasize theoretical over statistical significance.
AI Image Generation	DALL-E 2, Stable Diffusion, Midjourney, Firefly	Generates visuals for research, but may include copyrighted or misleading content.	Copyright infringement; data integrity issues; privacy risks.	Use ethically trained datasets; disclose AI-generated visuals; retain editable originals for verification.

The findings in Table 4 highlight both the opportunities and ethical risks of applying Generative AI (GenAI) tools in data analysis and visualization. In qualitative analysis, systems such as Claude 3 Opus and ChatGPT can efficiently generate codes, subthemes, and summaries of large datasets, supporting faster thematic exploration. However, these tools often fabricate supporting quotes or misattribute textual evidence, raising concerns about data fabrication, hallucination, and traceability (Lee et al., 2024; Perkins & Roe, 2024a). Such issues threaten the credibility of qualitative research, as fabricated or unverifiable data undermine the interpretive validity of findings. To mitigate these problems, researchers should maintain audit trails, manually verify generated content, and use GenAI tools only to assist—not replace—human analysis.

In quantitative analysis, GenAI-enabled tools such as ChatGPT (Python plugin) and Copilot demonstrate proficiency in performing statistical operations, modeling, and coding support. While these systems can enhance analytical speed and accessibility, they also risk promoting "p-hacking", bias amplification, and data manipulation, particularly when outputs are not rigorously validated (Head et al., 2015; Perkins & Roe, 2024b). The stochastic nature of AI-generated outputs further raises concerns about reproducibility, as identical prompts can yield differing statistical interpretations (Weber-Wulff et al., 2023). Researchers must therefore ensure transparency in data processing, document all AI-assisted steps, and replicate results using independent methods to maintain scientific reliability.

For AI image generation, tools like DALL-E 2, Stable Diffusion, Midjourney, and Firefly provide novel ways to visualize research findings but raise significant ethical issues, including copyright infringement, data integrity risks, and privacy concerns (Bendel, 2023). Generated visuals may contain copyrighted elements or misleading representations, compromising both scientific accuracy and legal compliance. As a result, researchers are urged to use ethically trained models—such as Adobe Firefly, which sources only licensed materials—and to provide clear disclosure of any AI-generated imagery used in publications (Meyer et al., 2024).

Programming and Code Generation

Table 5. Ethical Issues Related To Programming And Code Generation

Theme	Representative Tools	Key Findings / Observations	Ethical Issues Identified	Recommendations / Mitigation Strategies
Automated Code Generation	GitHub Copilot, OpenAI Codex, Tabnine, Claude	Produces runnable code but with	Licensing violations;	Develop test suites; review for vulnerabilities; check

		limited accuracy and security testing.	insecure code; plagiarism.	license compliance before use.
Programming Education	ChatGPT, Replit, Cursor	Enhances learning efficiency but may increase reliance on AI outputs.	Over-reliance; reduction in independent skill development.	Encourage critical engagement; use as scaffolding tool, not replacement for reasoning.

The findings in Table 5 reveal that Generative AI (GenAI) tools play an increasingly influential role in programming and code generation, improving productivity and learning efficiency but also introducing critical ethical and technical concerns. In automated code generation, platforms such as GitHub Copilot, OpenAI Codex, Tabnine, and Claude can produce runnable code snippets across multiple programming languages, substantially reducing development time. However, the generated code frequently suffers from limited accuracy, insufficient security validation, and potential licensing violations when outputs reproduce segments of copyrighted material from non-free repositories (Yetiştiren et al., 2023; Poldrack et al., 2023). Moreover, the lack of transparency regarding model training data raises questions about plagiarism and intellectual property rights, as users may unknowingly distribute code derived from proprietary sources. Researchers and developers are therefore encouraged to conduct rigorous testing, apply secure coding practices, and verify code provenance before deployment (Martin, 2008; Perkins & Roe, 2024).

In programming education, GenAI systems such as ChatGPT, Replit, and Cursor have demonstrated clear pedagogical benefits, notably in enhancing learning efficiency and supporting novice programmers with real-time feedback and debugging assistance (Kazemitabaar et al., 2023). However, this convenience comes with the risk of over-reliance on AI-generated solutions, which may hinder the development of independent problem-solving and coding skills (Uplevel, 2024). Ethical teaching practices should emphasize AI literacy, guiding students to critically evaluate AI-generated outputs and use them as learning aids rather than complete substitutes for human reasoning.

Overall, while GenAI offers transformative advantages for software development and programming education, its integration must be guided by accountability, transparency, and pedagogical responsibility. Human oversight, proper citation of AI-generated code, and explicit awareness of licensing constraints are essential to maintain technical integrity and ethical compliance in AI-assisted programming (ALLEA, 2023; Weber-Wulff et al., 2023).

Academic Writing, Editing, and Translation

Table 6. Ethical issues related to Academic Writing, Editing, and Translation

Theme	**Representative Tools**	**Key Findings / Observations**	**Ethical Issues Identified**	**Recommendations / Mitigation Strategies**
Grant Proposal Writing	ChatGPT, Claude, Copilot	Aids structure and style but may dilute originality and leak sensitive ideas.	Confidentiality breach; idea plagiarism.	Use local instances; avoid uploading unpublished proposals; disclose AI use.
Text Generation	ChatGPT, Gemini, Grok, Kahubi	Enables content creation but risks hallucination and academic freedom restrictions.	Misinformation; censorship; bias; authorship ambiguity.	Fact-check all content; ensure transparency; maintain academic freedom and authorship integrity.
Text Editing & Proofreading	PaperPal, Grammarly, WordTune	Improves clarity but can distort meaning or remove citations.	Plagiarism by paraphrase;	Conduct human review after editing; lock

			grammatical inconsistencies.	technical terms; recheck all citations.
Translation	DeepL, Google Translate, ChatGPT, BERT	Facilitates multilingual research but inconsistent in rare languages.	Cultural/semantic bias; detector false positives.	Apply post-editing by bilingual experts; avoid AI detectors on translated text.

The findings presented in Table 6 show how Generative AI (GenAI) systems have become integral to academic writing, editing, and translation, offering substantial productivity gains while simultaneously introducing new ethical vulnerabilities. In grant proposal writing, tools such as ChatGPT, Claude, and Copilot assist researchers in improving structure, tone, and stylistic consistency. However, these tools also risk breaching confidentiality, particularly when users upload unpublished proposals or sensitive intellectual property to cloud-based servers (Perkins & Roe, 2024). Furthermore, over-reliance on AI-driven phrasing may dilute originality and lead to inadvertent idea plagiarism (Moulin, 2023). To mitigate such risks, researchers should rely on local AI deployments, avoid sharing confidential drafts online, and explicitly disclose AI use in funding submissions (ALLEA, 2023).

In text generation, models like ChatGPT, Gemini, Grok, and Kahubi can generate fluent academic prose, aiding in idea development and draft expansion. Nonetheless, their tendency to hallucinate references, promote censorship bias, and create authorship ambiguity poses significant threats to academic integrity (Weber-Wulff et al., 2023). As GenAI models are trained on unevenly distributed data, they can unconsciously reproduce ideological or linguistic biases that undermine academic freedom and transparency (Perkins & Roe, 2024). To address this, all AI-generated content should undergo human fact-checking and authorship verification, ensuring that credit attribution remains accurate and verifiable.

For text editing and proofreading, AI tools such as PaperPal, Grammarly, and WordTune enhance linguistic accuracy and stylistic fluency but may inadvertently distort meaning or remove essential citations, leading to plagiarism by paraphrase or grammatical inconsistencies (Lorenz et al., 2023). Ethical practice requires post-editing by human experts, particularly in technical disciplines where terminology precision is critical. Scholars should also maintain careful control over citation management to preserve traceability and accountability in revised texts.

Finally, in translation, systems such as DeepL, Google Translate, ChatGPT, and BERT play a pivotal role in facilitating multilingual research dissemination, especially for scholars writing in non-dominant languages. However, these tools remain inconsistent in low-resource or rare languages and may introduce cultural or semantic biases, resulting in false positives in AI detection systems (Castro et al., 2024). Consequently, translated texts should undergo post-editing by bilingual experts, and researchers should avoid AI detection tools when evaluating translated content to prevent unjustified academic penalties.

Overall, GenAI tools are transforming academic writing by promoting accessibility, efficiency, and multilingual collaboration. Yet, responsible integration requires a firm commitment to ethical transparency, originality, authorship integrity, and cultural sensitivity to ensure that technological assistance strengthens—rather than undermines—the credibility of scholarly communication (ALLEA, 2023; Perkins & Roe, 2024; Weber-Wulff et al., 2023).

RECOMMENDATIONS

Based on the synthesis of findings across all research stages—from literature gathering to academic writing—this section outlines key recommendations for the ethical, transparent, and effective integration of Generative AI (GenAI) tools in academic research. These recommendations are organized around four guiding principles: accountability, accuracy, authorship integrity, and ethical governance.

Promote Human Oversight and Accountability

While GenAI systems such as ChatGPT, Claude, and Copilot offer powerful assistance in research design, data processing, and manuscript writing, they should function as supporting tools rather than autonomous decision-makers. Human oversight must remain central in every stage of the research workflow—from verifying AI-generated references to reviewing analytical outputs and editing manuscripts (Perkins & Roe, 2024; Weber-Wulff et al., 2023). Institutions should develop clear AI accountability frameworks, requiring researchers to document when and how AI systems are used, along with human verification steps undertaken to ensure research integrity.

Ensure Accuracy, Transparency, and Reproducibility

Given the well-documented risks of AI hallucinations, fabricated citations, and inconsistent reproducibility in GenAI outputs (Liu et al., 2023; Head et al., 2015), researchers must apply rigorous validation strategies. These include cross-checking references, re-analyzing AI-derived data manually, and retaining transparent records of prompt histories and outputs. Journals and funding bodies should mandate disclosure statements specifying the extent and purpose of AI use in research and writing.

Safeguard Intellectual Property and Data Privacy

Researchers must exercise caution when uploading materials—particularly unpublished manuscripts, confidential data, or proprietary datasets—to GenAI platforms. Many tools' terms of service permit data reuse for model training, creating risks of intellectual property (IP) transfer and data breaches (Bakos et al., 2014; Journal of Urology, 2025). To mitigate this, institutions should prioritize local or institutionally hosted AI systems that comply with data protection regulations such as GDPR and ensure explicit informed consent when human subjects' data are involved.

Reinforce Ethical Research Design and Participant Protection

In study design and data collection, GenAI may inadvertently generate biased or culturally insensitive survey questions or misinterpret ethical nuances (Perni et al., 2023). Ethics committees should therefore maintain human-led reviews and adopt AI ethics checklists to assess potential harms related to bias, discrimination, or participant autonomy. Moreover, informed consent statements generated with AI must undergo human validation to avoid misinformation or vague disclosures (Currie et al., 2023).

Support Responsible AI Use in Education and Writing

In teaching and academic writing, the overuse of GenAI tools can hinder the development of independent reasoning and critical thinking (Kazemitabaar et al., 2023; Uplevel, 2024). Educators should integrate AI literacy programs into curricula, emphasizing critical engagement, bias recognition, and citation ethics. In academic publishing, researchers should treat GenAI outputs as assistive drafts, not as final text, and perform manual fact-checking and sensitivity review for topics involving historical trauma, marginalized groups, or politically sensitive issues (Resnik & Hosseini, 2023; Waddington, 2024).

Develop Institutional and Disciplinary Guidelines

Universities, funding agencies, and publishers should collaboratively develop discipline-specific AI use policies that balance innovation with ethical responsibility. These policies should define acceptable use cases (e.g., grammar correction, summarization), mandate AI use disclosure, and prohibit plagiarism or AI-assisted peer review without consent (COPE, 2023). A global standard aligned with the ALLEA (2023) Code of Research Integrity could promote consistency in addressing authorship, accountability, and transparency concerns across research contexts.

Encourage Collaboration Between AI Developers and Researchers

Finally, fostering partnerships between AI developers and academic institutions can promote ethical model training, reduce data bias, and improve domain-specific accuracy. Co-developing open-access AI systems trained on peer-reviewed scientific literature—rather than uncontrolled internet data—could enhance reliability while safeguarding research integrity (Meyer et al., 2024).

In summary, while Generative AI holds immense potential to advance research efficiency, creativity, and accessibility, its ethical deployment demands continuous vigilance, transparency, and education. The future of responsible AI-assisted scholarship depends on balancing technological innovation with human judgment, ensuring that these tools enhance—not erode—the values of integrity, originality, and intellectual rigor that define academic research.

CONCLUSION

This study provides a comprehensive examination of how Generative Artificial Intelligence (GenAI) is reshaping the research landscape across multiple stages of the academic process—from literature gathering and study design to data analysis, code generation, and academic writing. Drawing on a practice-informed rapid review and a series of tool-based probes, the findings highlight a clear duality: while GenAI offers unprecedented efficiency, accessibility, and creative support, it simultaneously raises profound ethical, methodological, and epistemological challenges.

Across the research lifecycle, GenAI demonstrates strong capabilities in automating repetitive tasks, enhancing multilingual collaboration, and improving communication for non-native English speakers. However, recurring issues such as fabricated citations, data privacy risks, bias reinforcement, and authorship ambiguity underscore the persistent need for human oversight and ethical governance. Particularly concerning are the threats to academic freedom, intellectual property integrity, and research transparency, which emerge from the opaque and probabilistic nature of large language models (Perkins & Roe, 2024; Weber-Wulff et al., 2023).

The study also shows that ethical risks are unevenly distributed across the research process. Early stages such as literature gathering and summarization suffer from misinformation and copyright transfer risks, while later stages like data analysis and image generation reveal reproducibility issues and potential data fabrication. In writing and translation, GenAI supports stylistic and linguistic refinement but risks diluting originality and introducing semantic or cultural bias. These findings emphasize that the utility of GenAI must be balanced with principled restraint and critical reflection.

Ultimately, the responsible use of GenAI in research depends on embedding transparency, accountability, and human critical judgment at every step of the academic workflow. Institutions, publishers, and funding agencies must implement clear policies, disclosure requirements, and AI literacy programs to guide ethical use. As AI continues to evolve, researchers must move beyond simple adoption toward ethical adaptation, ensuring that technology complements rather than compromises the rigor and trustworthiness of scientific inquiry.

In essence, GenAI should be viewed not as a replacement for human intellect, but as a catalyst for more reflective, equitable, and ethically grounded scholarship. Only through continuous dialogue, critical evaluation, and collective responsibility can the academic community harness AI’s transformative potential while safeguarding the fundamental values of integrity, originality, and academic freedom that underpin the pursuit of knowledge.

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