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Navigating the Future: Attitudes and Ethical Implications of AI Tools in Academic Research

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ABSTRACT

The growing use of artificial intelligence (AI) tools is transforming traditional research methods, making them more efficient, accurate, and innovative. This paper examines the awareness, usage, and ethical concerns of AI tools among postgraduate students and research scholars from various fields. This quantitative descriptive study looks into how postgraduate students and PhD researchers view the benefits, challenges, and ethical issues related to AI tools in research. A key finding is that, despite high familiarity with AI, less than one in five users utilize data-mining, predictive modeling, or visual analytics platforms. Participants rated AI's contribution to research quality highly but reported only monthly use, showing underuse despite recognizing its value. AI tools save time and boost efficiency and accuracy. Still, challenges such as insufficient training, ethical uncertainties, and technical issues remain. The study suggests that universities include workshops, data ethics courses, and discipline-specific guidelines to encourage responsible AI integration and promote open, transparent AI development. It also highlights the need for AI developers to be clearer about data ownership and algorithmic bias.

Keywords: Artificial Intelligence (AI), Academic Research, Postgraduate Students, Research Scholars, Ethical Implications, AI Awareness and Utilisation

INTRODUCTION

Artificial intelligence (AI) is rapidly changing the landscape of academic research by automating time-consuming tasks and allowing researchers to spend more time to critical thinking and innovation. Researchers, especially postgraduate students, face significant challenges, including time limitations, balancing research with teaching, and staying updated with an overwhelming body of literature. AI tools are increasingly used to accelerate literature reviews, improve data analysis and enhance academic writing across disciplines from the sciences to the humanities. For example, AI tools like *Litmaps* and *Powerdrill* use algorithms to scan academic texts, identify key themes, research trends, and gaps in the literature (Torre-López et al., 2023; Wagner et al., 2021). By streamlining literature reviews, AI tools enable researchers to focus on synthesizing information and developing new ideas instead of spending time on tedious tasks (Snyder, 2019; Xiao & Watson, 2017). Furthermore, AI enhances various aspects of the research process by integrating data, literature, and statistical analysis from multiple sources (Tovar, 2023).

Additionally, tools like *Tableau* and *R* analyze large data sets to create visual presentations of complex results that help understand study outcomes (Hohman et al., 2019; Leite et al., 2020). This process of converting raw data into understandable visuals ensures that researchers make better decisions (Injadat et al., 2021). AI writing tools such as language models (LLMs), Grammarly, and QuillBot make research activities easier and more affordable by enhancing academic writing, assisting with composition, and reducing language barriers, especially for non-native English speakers (Lin, 2024). Among these innovations, ChatGPT has gained notable attention for its speed, efficiency, and ability to generate prompt, informative responses. Its real-time processing allows for smooth, engaging interactions, making it a valuable resource for researchers seeking immediate support (Samala et al., 2025). Its conversational interface and capability to operate in multiple languages have made it particularly accessible to a global community of postgraduate students and researchers (Chan & Hu, 2023; De Angelis et al., 2023; Roumeliotis & Tselikas, 2023). These tools also assist non-native English speakers in understanding academic writing conventions (Saberi et al., 2020; Shi, 2022).

Nevertheless, integrating AI into academic research raises important ethical and practical issues that are especially relevant for postgraduate students and research scholars. Key concerns include data privacy, compliance with regulations like the GDPR, algorithmic bias, and the risk of becoming too dependent on automation (Balta, 2023; d'Aquin, 2018; Lu, 2022). These issues could cause a decline in vital research skills such as critical thinking and analytical reasoning (Asagar, 2025; Gendron et al., 2022; Mohammadkarimi, 2023). They highlight the need for ethical AI use to ensure that technological progress does not compromise research integrity or essential scholarly skills (Chubb et al., 2021; Cui, 2021; Dave & Patel, 2023). Furthermore, biases built into AI algorithms can reinforce existing biases in research outputs, challenging efforts to maintain fairness and accuracy (Mikołajczyk-Bareła & Grochowski, 2024). Recent scoping reviews point out that misinformation and negative human-computer interactions are among the most urgent ethical issues in higher education settings (Li et al., 2024). While AI tools provide significant benefits, they lack the personalization and human empathy found in genuine human interactions. Their inability to fully grasp user context can result in generic or irrelevant responses, which limits the depth and nuance of communication (Samala et al., 2025). An important yet often overlooked concern is the ownership and authorship of AI-produced content. The Terms of Service (ToS) of many commercial AI platforms may claim certain rights over user-uploaded data, raising potential conflicts over intellectual property and academic ownership (Gendron et al., 2022; Lauer, 2023).

Although AI's growing role in education and teaching continues, few studies examine its adoption and ethical issues among researchers, especially in developing countries or emerging research fields. As researchers are essential for fostering innovation and generating knowledge, understanding their needs, perceptions, and challenges related to AI adoption is crucial. This study addresses that gap by exploring researchers' awareness, usage habits, and ethical concerns regarding AI tools. The findings help educational institutions, policymakers, and research communities understand the specific barriers researchers face and the institutional support needed to encourage responsible and effective AI use. It also highlights the shared responsibility between academic institutions and AI developers to ensure ethical and transparent AI practices.

RESEARCH METHODOLOGY

Research Design

This study adopts a quantitative descriptive research design. While Likert scales capture subjective perceptions (e.g., attitudes, awareness), the numerical coding of responses (1–5 scales) and statistical analysis (means, SDs, percentages) classify this as a quantitative study. Descriptive statistics summarise patterns in awareness, usage, and ethical concerns, aligning with quantitative approaches. Descriptive statistics offer a summarised view of trends and distributions, which aligns with the aim of this research to provide a foundational understanding rather than inferential generalisation (Kumar, 2025).

Population and Sampling

This study comprised 66 respondents, including both PhD and postgraduate students from the Department of Education at a central university in Delhi. Initially, participants were recruited through convenience sampling. Subsequently, purposive sampling was used to narrow the sample based on the inclusion criterion of active use of artificial intelligence (AI) tools in research, identified through the screening question: *"Have you ever used AI in your research?"* This process resulted in **53 valid respondents** who actively use AI tools in their research.

The total number of PhD and postgraduate students in the Department of Education is approximately **200**. Therefore, the final sample comprises about **26.5% of the entire population**, providing a solid basis for analysis in exploratory research. According to the **Central Limit Theorem (CLT)**, a sample size of 30 or more is generally enough for the sampling distribution of the mean to become approximately normal (Field, 2013). Since the sample size of 53 surpasses this threshold and considering the purposive focus on AI users, the sample is methodologically appropriate for the intended analyses.

While the sample is limited to a single university which may limit external validity and generalizability, the study emphasizes **internal validity and contextual depth** by focusing on participants with firsthand experience using AI in academic research. Future research could build on these findings by including larger, multi-institutional samples to improve representativeness and enable inferential statistical comparisons.

Instrumentation Development and Validation

The primary data collection instrument was a self-administered questionnaire designed to capture quantitative insights into participants' awareness, usage, and ethical considerations related to AI tools. The **questionnaire** was developed through a rigorous process:

1. **Literature Review**: Questionnaire items were **adapted from validated instruments** used in prior studies on AI adoption in education and research contexts (e.g., (Chubb et al., 2021; Samala et al., 2025)). The items were contextualised to fit academic research settings, particularly for research scholars.
2. **Content Validity**: A draft version of the questionnaire was reviewed by **two domain experts** in educational technology and AI ethics. Feedback included:
    1. Clarifying ambiguous terms such as "advanced AI tools" by listing examples (e.g., ChatGPT, Grammarly, Scite).
    2. Adding context-specific response options for AI usage frequency and purpose.
    3. Ensuring construct alignment for each section.

Their suggestions were incorporated, and a second review confirmed that the revised tool was appropriate in scope and clarity.

3. **Pilot Testing**:
    1. A **pilot study** involving **ten participants** (excluded from the final analysis) was conducted to evaluate the questionnaire's clarity, coherence, and completion time.

2. Reliability analysis of the pilot and final instruments produced the following **Cronbach's alpha values**, all of which fall within acceptable ranges:
    1. **Awareness**: α = 0.702
    2. **Usage**: α = 0.700
    3. **Benefits and Challenges**: α = 0.710
    4. **Ethical Considerations**: α = 0.743

These scores indicate **acceptable internal consistency**, supporting the instrument's reliability (Tavakol & Dennick, 2011).

Instrument Structure

The questionnaire consisted of closed-ended questions organised into three main sections corresponding to the study's objectives:

1. **Awareness of AI Tools**: This section included Likert-scale questions to assess familiarity, training, and confidence in using AI tools for research purposes. The internal consistency of this tool was acceptable, with a Cronbach's alpha of **0.702**.
2. **Usage of AI Tools**: Questions in this section explored the frequency and purpose of AI tool usage, as well as their perceived impact on research quality and efficiency. This tool demonstrated acceptable reliability, with a Cronbach's alpha of **0.700**.
3. **Benefits and Challenges of AI Tools**: Questions in this section explored the frequency of AI tool usage, benefits and challenges. This tool demonstrated acceptable reliability, with a Cronbach's alpha of **0.710**.
4. **Ethical Considerations**: This section examined concerns such as plagiarism, data privacy, and bias in AI tools and included questions on how participants address these issues. The reliability of this tool was also acceptable, with a Cronbach's alpha of **0.743**.

Additionally, multiple-response questions were included to identify specific tools and resources used by participants.

DATA COLLECTION AND ANALYSIS

Researchers shared the survey form digitally with participants through Google Forms during October and November 2024, ensuring simple and convenient access for all. The data were analysed using statistical software SPSS (V.27), producing descriptive statistics such as means, standard deviations, and percentages that were computed to summarise trends across key variables. The analysis data appeared in tabular form.

To ensure consistency across Likert-scale formats (some being 4-point and others 5-point), responses were standardised. This was achieved by calculating the range of each scale (maximum – minimum) and dividing it by the maximum value, resulting in values such as 0.8 for 5-point scales and 0.75 for 4-point scales. This method ensured cross-sectional comparability and prevented distortion due to scale variation.

This section organises the study's findings according to each specific objective. The relevant analyses for each objective and discuss the corresponding outcomes in detail.

O1: Awareness of AI tools among respondents

Table 1: Responses on Awareness Regarding AI Tools in Academic Research

Statements	Mean	SD	Range	Maximum
How familiar are you with the AI tools available for academic research?	3.77	0.869	4	5
Do you know how to access and use AI tools relevant to your research field?	3.17	1.033	3	4
Have you been introduced to the concept of AI tools in your coursework or research training?	2.43	0.888	3	4
Do you believe that understanding AI tools is essential for your research?	4.3	0.822	4	5
How confident are you in your ability to evaluate the quality and reliability of AI tools used in research?	3.87	0.761	4	5

Table 1 presents responses regarding respondents' awareness and understanding of AI tools in academic research. The majority of the respondents, as indicated by a mean score of 3.77 (SD = 0.869), which can be categorised as a moderate score, emphasised their “somewhat familiar” status with AI tools used for the purposes of academic research. However, when asked whether they knew how to access and use AI tools relevant to their research field, the mean score was lower at 3.17 (SD = 1.033), suggesting that while respondents are generally aware of how to access these tools, they feel they need further assistance in using them effectively. Respondents reported a mean score of 2.43 (SD = 0.888) for formal training, which pointed out that quite a few AI tools have been exposed in professional environments. Despite this, a mean score of 4.3 (SD = 0.822) shows that respondents are strongly agree that understanding AI tools is essential for their research. Lastly, respondents were ‘somewhat confident’ in their ability to assess the quality and trustworthiness of AI tools, with the respondents establishing a mean of 3.87 (SD = 0.761).

Table 1.1: Participants' Awareness of AI Tools and Preferred Support Resources for Using AI in Research.

Statements	**Options**	**%**
Which of the following AI tools are you aware of?	Natural Language Processing (e.g., Grammarly, ChatGPT)	98.1%
	Data analysis tools (e.g., IBM Watson, Tens or Flow)	15.1%
	Literature review tools (e.g., Iris.ai, Research Rabbit)	18.9%
	Predictive modeling tools (e.g., Google Cloud AI, Azure AI)	18.9%
	DALL·E	1.9%
	None	0.0%
Support or resources would help you better understand and use AI tools in your research	Workshops or Seminars	61.5%
	Online Tutorials or Courses	53.8%
	Guidance from faculty or mentors	38.5%
	Access to AI tool experts	30.8%
	None	5.8%

Table 1.1 presents the percentage of respondents who are aware of various AI tools. A substantial majority (98.1%) of respondents are familiar with natural language processing tools (e.g., Grammarly, ChatGPT), indicating the widespread use and recognition of these tools. 15.1% of respondents said they were familiar with data analysis tools (like IBM Watson and TensorFlow), and 18.9% said they were familiar with literature review tools (like Iris.ai and Research Rabbit). Similarly, 18.9% of respondents recognised predictive modelling tools such as Google Cloud AI and Azure AI. The least recognised tool was DALL·E, with just 1.9% of respondents indicating awareness. Interestingly, no respondents reported being completely unaware of AI tools, as shown by 0% in the "None" category.

Furthermore, Table 1.1 outlines the types of support or resources respondents feel would help them better understand and use AI tools in their research. The majority of respondents (61.5%) expressed interest in workshops or seminars as a resource for improving their understanding of AI tools. Online tutorials or courses were also considered valuable by 53.8% of respondents. A notable portion (38.5%) indicated that guidance from faculty or mentors would be beneficial, while 30.8% suggested that access to AI tool experts would assist them in utilising AI tools more effectively. A smaller group (5.8%) felt that they would not require any additional resources to better understand AI tools.

Interpretation

The findings reveal a moderate level of awareness of AI tools among respondents, with 3.77 as the mean score for general familiarity. However, this awareness appears to be **surface-level**, as practical knowledge of how to access and use these tools is notably lower (M = 3.17), and formal exposure through training is minimal (M = 2.43). Despite limited hands-on experience, respondents strongly agreed (M = 4.3) that understanding AI tools is essential for academic research, indicating a **recognition of importance but a gap in preparedness**.

A closer look at specific tools (Table 1.1) highlights that nearly all respondents (98.1%) are aware of **natural language processing tools** like ChatGPT and Grammarly—tools that are accessible, user-friendly, and integrated into everyday academic writing. In contrast, more technical tools—such as data analysis platforms (15.1%) or predictive modelling tools (18.9%)—are far less recognised. Awareness of creative AI tools like DALL·E was negligible (1.9%), reflecting a **narrow functional awareness** of AI, centered around language-related tasks.

Support needs expressed by respondents (Table 1.2) align with this limited engagement. A majority (61.5%) called for **structured interventions** such as workshops and seminars, followed by online tutorials (53.8%). The relatively low scores for expert access (30.8%) and faculty guidance (38.5%) may indicate **limited institutional or mentorship-based support** for AI integration into research workflows.

Taken together, these results suggest that while respondents acknowledge the value of AI in research, their awareness is **concentrated around accessible, writing-focused tools**, and **deeper engagement is hindered by a lack of formal training and institutional support**. There is a pressing need for targeted educational initiatives to bridge this awareness-to-application gap, especially for advanced and data-driven AI tools.

O2: Usage of AI Tools in Academic Research

Table 2: Responses on Usage of AI Tools in Academic Research

Statements	Mean	SD	Range	Maximum
How frequently do you use AI tools in your research?	2.77	1.068	3	4
How effective were the AI tools in supporting the presentation of papers?	3.08	0.895	4	5
How did the AI tools impact the clarity and effectiveness of paper presentations?	3.34	0.678	3	5

How has AI impacted the quality of your research?	4.21	0.743	4	5

Table 2 shows the responses regarding the application of AI tools in research. Respondents indicated that they utilised AI tools in their research "monthly", achieving a mean score of 2.77 (SD = 1.068). AI tools were rated moderately useful (M=3.08; SD=0.895) for paper presentations. Although they were perceived as enhancing the research presentation, their impact differed, as indicated by the standard deviation. The assessment of AI tools on the clarity and effectiveness of paper presentations yielded a mean score of 3.34 (SD = 0.678), suggesting a "moderate impact". The overall impact of AI on research quality received a high mean score of 4.21 (SD = 0.743), suggesting that respondents believed AI tools "significantly enhanced" the quality of their research.

Table 2.1 Primary Purposes and Frequently Used AI Tools in Research

Category	Item	%
Primary Purposes of AI in Research	Data Collection and Analysis	30.2%
	Writing Assistance (drafting, Grammar, etc.)	79.2%
	Literature Review	56.6%
	Predictive Modelling or Simulations	7.5%
	Experimental Design	9.4%
	Hypothesis Generation	9.4%
	Paper Writing and Editing	32.1%
	Predictive Modelling	3.8%
	Learning About Topics from AI	3.8%
	N/A	0.0%
Frequently Used AI Tools in Research	ChatGPT	86.8%
	Google Gemini	39.6%
	Research Kickstart	3.8%
	Grammarly	62.3%
	QuillBot	60.4%
	Microsoft Copilot	13.2%
	PDF.ai	7.5%
	Consensus	1.9%
	WordAi	5.7%
	Research Rabbit	7.5%
	N/A	1.9%

Table 2.1 highlights respondents' usage of different AI tools in their research[1]. Use of AI tools is heavily skewed toward natural language processing (94.3%), with limited adoption of more technical tools like data analysis (9.4%) and predictive modelling, suggesting a gap in technical skill or accessibility. Reference tools (e.g., Google Scholar, Zotero, Mendeley, and EndNote) were also frequently used, with 47.2% of respondents selecting them, indicating their utility in managing citations and references. 18.9% of respondents used research paper summariser tools (e.g., Scholarcy, POPAi) and predictive modelling tools (e.g., Google Cloud AI, Azure AI), indicating a moderate engagement with these tools. 13.2% of respondents used literature review tools such as Iris.ai and Research Rabbit, and another 13.2% employed AI-powered research paper writing assistants.

Table 2.1 also explores the primary purposes for which respondents use AI tools in their research. The most common use is for writing assistance, with 79.2% of respondents using AI for tasks like drafting and grammar checks. Literature Review is another significant area, with 56.6% of respondents using AI tools for this purpose, reflecting the tools' role in enhancing research efficiency and knowledge gathering. Data collection and analysis was the primary purpose for 30.2% of respondents, while 32.1% use AI for paper writing and editing. Only 7.5% and 9.4% of respondents, respectively, said they used AI tools for predictive modeling or simulations and experimental design. These were the least common uses. Hypothesis Generation also saw lower engagement, with 9.4% using AI tools for this purpose. Learning about topics from AI was reported by 3.8%, showing that some respondents rely on AI for general knowledge acquisition. The "N/A" category was marked by 0%, indicating that all respondents selected at least one-use case.

There is a list of the AI tools that respondents frequently use in their research. ChatGPT is the most frequently used tool, with 86.8% of respondents utilizing it regularly, likely for its versatile capabilities in writing, summarizing, and generating ideas Grammarly comes in second with 62.3% of respondents, highlighting its significance in ensuring high-quality writing. QuillBot was also widely used by 60.4% of respondents, likely for paraphrasing and improving text fluency. Google Gemini was used by 39.6% of respondents, indicating a moderate adoption of this newer AI tool. Other tools such as Microsoft Copilot (13.2%), Research Kickstart (3.8%), and PDF.ai (7.5%) were less frequently used. Specialized tools like Consensus (1.9%) and Research Rabbit (7.5%) had lower usage rates, with Consensus being used by a small minority. The N/A category was minimal, with only 1.9% indicating no frequent use of AI tools.

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[1] DALL·E (an image-generation tool) was included in awareness tables because participants recognized it as an AI tool. However, it was excluded from usage tables since none of the respondents reported applying it to text-based academic research.

The data indicates moderate but uneven adoption of AI tools in academic research. Respondents reported using AI tools infrequently (M = 2.77), primarily on a monthly basis, which suggests that while awareness is high, actual usage is not yet embedded into daily research workflows. Despite this, AI tools are viewed as having a substantial positive impact on research outcomes, particularly in improving research quality (M = 4.21), clarity of presentation (M = 3.34), and presentation support (M = 3.08). These results highlight a disconnect between usage frequency and perceived utility.

Tool usage patterns (Table 2.1) reinforce this observation. A significant 94.3% of respondents reported using natural language processing (NLP) tools like ChatGPT and Grammarly, underscoring a strong preference for writing-enhancement tools. In contrast, technically demanding tools such as data mining and predictive modeling systems were used by fewer than 20% of respondents, pointing to limited engagement with data-intensive or analytical AI functions. Similarly, tools for summarising, literature reviews, or paper generation remain underutilised, suggesting that most AI usage is still confined to surface-level writing support.

The purpose-specific data (Table 2.2) mirrors these patterns. Writing assistance (79.2%) and literature review support (56.6%) were the most common uses, while experimental design (9.4%), hypothesis generation (9.4%), and predictive modelling (7.5%) were rarely cited. This demonstrates that AI is primarily viewed as a support tool rather than a driver of scientific innovation or analytical thinking.

In terms of tool preference, ChatGPT dominates usage (86.8%), followed by Grammarly (62.3%) and QuillBot (60.4%), all of which focus on language refinement and paraphrasing. In contrast, tools intended for deeper research tasks (e.g., Consensus, Research Kickstart, PDF.ai) saw very limited use, suggesting that researchers gravitate toward tools with low learning curves and immediate utility, rather than those requiring integration into complex research workflows.

O3: Benefits and Challenges among Respondents

Table 3 outlines the benefits that respondents associate with using AI in research. Time savings emerged as the most significant benefit, with 75.5% of respondents acknowledging that AI tools help save valuable time in their research processes. Increased efficiency was the second most cited benefit, with 64.2% of respondents noting that AI tools enable them to work more efficiently. Improved accuracy was also recognised by 50.9% of respondents, reflecting AI's contribution to reducing errors in research tasks. Better research insights were noted by 43.4%, indicating that AI tools can help respondents uncover deeper or more relevant findings. Enhanced data analysis capabilities were reported by 28.3% of respondents, pointing to AI’s role in handling and interpreting complex data. Finally, a small group of respondents (3.8%) reported no major impact from using

AI tools, suggesting that while the majority see tangible benefits, a few did not perceive significant advantages.

Table 3: Benefits and Challenges of Using AI in Research

Category	Item	%
Benefits Experienced from Using AI in Research	Increased efficiency	64.20%
	Improved accuracy	50.90%
	Enhanced data analysis capabilities	28.30%
	Time savings	75.50%
	Better research insights	43.40%
	No major impact	3.80%
Challenges Faced When Using AI in Research	Technical difficulties	49.10%
	Lack of training or knowledge	52.80%
	Data privacy and security issues	43.40%
	Ethical concerns	54.70%
	Integration with existing tools	20.80%
	High cost	32.10%

Table 3 also outlines the challenges that respondents encounter when using AI tools in their research. Lack of training or knowledge emerged as the most significant challenge, with 52.8% of respondents indicating that they face difficulties due to insufficient training in AI tools. Ethical concerns were the second most commonly cited challenge, with 54.7% of respondents expressing apprehension about the ethical implications of AI in research. Technical difficulties were reported by 49.1% of respondents, highlighting issues with the functionality or usability of AI tools. Data privacy and security issues were cited by 43.4%, indicating concerns about how AI tools manage sensitive or personal data. High cost was also a challenge for 32.1% of respondents, suggesting that affordability may be a barrier to broader adoption of certain AI tools. Integration with existing tools was less of a concern, with only 20.8% reporting issues in integrating AI tools with their current research infrastructure.

Perceived benefits of AI were clear: time savings (75.5%), increased efficiency (64.2%), and improved accuracy (50.9%) were top-ranked, highlighting that researchers value AI primarily for its productivity-enhancing qualities. However, only 28.3% recognised benefits in data analysis, and 3.8% saw no major impact—emphasising again that the transformative potential of AI in deep research tasks remains underexplored by most respondents.

Respondents acknowledge the usefulness of AI in research and report meaningful benefits, but their actual usage remains concentrated in low-barrier, writing-focused applications, with minimal integration into the analytical or generative aspects of the research process. This reveals a pressing need for targeted capacity-building initiatives that go beyond tool awareness to promote deeper, discipline-specific application of advanced AI tools.

Reported challenges reinforce this interpretation. While ethical concerns (54.7%) and lack of training (52.8%) were the most frequently cited difficulties, only a minority (28.3%) actively engaged in reviewing AI models for bias or consulted ethics committees (17%). This gap between perceived risks and proactive mitigation strategies suggests that although concerns are recognised, formal ethical frameworks and capacity-building mechanisms are lacking.

O4: Ethical Concerns among Respondents

Table 4.1: Responses on Ethical Consideration of AI Tools in Research

Statements	Mean	SD	Range	Maximum
Plagiarism risk (AI-generated content being unoriginal)	3.49	1.28	4	5
Bias in AI algorithms affecting research outcomes	3.26	1.258	4	5
Data privacy and security when using AI	3.6	1.214	4	5
Over-reliance on AI reducing critical thinking	3.79	1.183	4	5
Ownership and authorship of AI-generated content	3.32	1.312	4	5
Do you believe that using AI tools could lead to unintentional plagiarism in research?	4.13	0.81	4	5
How confident are you in distinguishing between your original research work and AI-assisted content?	3.75	1.054	4	5

Table 4.1 presents responses concerning the ethical implications of using AI tools in research. Concerning the risk of unoriginal content stemming from automated generation, respondents indicated a mean score of 3.49 (SD = 1.28), reflecting a "moderate concern" about the possibility of tools producing material that lacks complete originality. The notable standard deviation indicates a significant variation in respondents ' perceptions of this risk. The mean score regarding bias in AI algorithms impacting research outcomes was 3.26 (SD =

1.258), indicating that respondents express a somewhat concern about the potential influence of biases in AI algorithms on their research results. Once more, the standard deviation highlights the variability in the level of concern expressed by the respondents.

Respondents showed a moderate level of concern regarding data privacy and security in the context of AI usage, achieving a mean score of 3.6 (SD = 1.214). The apprehension about excessive dependence on AI affecting critical thinking was notably elevated, with a mean score of 3.79 (SD = 1.183). The mean suggests that respondents express a "moderate concern" regarding the risk of becoming too reliant on AI tools, potentially hindering their capacity for independent and critical thought. Regarding the ownership and authorship of content generated by artificial intelligence, the average score was 3.32 (SD = 1.312), indicating that respondents express a somewhat concern about the implications of AI in establishing ownership and credit for research outputs that involve AI assistance. Respondents expressed agreement with the potential for AI tools to inadvertently result in plagiarism during research, achieving a mean score of 4.13 (SD = 0.81). Finally, regarding the ability to differentiate apart original research from AI-assisted material, the mean score of 3.75 (SD = 1.054) suggests that respondents feel "somewhat confident" in distinguishing their own work from content produced by AI, although a degree of uncertainty remains.

Table 4.2: Ethical Considerations Addressed in AI Research

How do you address the ethical considerations associated with AI in your research?	**In Percentage**
Adhering to ethical guidelines	66.00%
Using anonymized data	24.50%
Consulting with ethics committees	17.00%
Regularly reviewing AI models for bias	28.30%
Not come across such issues	3.80%

Table 4.2 outlines the ethical considerations that respondents prioritize when using AI tools in their research. The most frequently reported ethical consideration is adhering to ethical guidelines, with 66.0% of respondents emphasizing the importance of following established ethical standards in AI research. Using anonymized data was considered important by 24.5% of respondents, reflecting the growing awareness of data privacy issues, although it was less frequently cited than other concerns. Regularly reviewing AI models for bias was a priority for 28.3% of respondents, underscoring the need for ongoing evaluation of AI systems to ensure they are not perpetuating bias. Consulting with ethics committees was seen as necessary by 17.0%, suggesting that a smaller group

of respondents actively seeks formal ethical guidance in their research. Lastly, 3.8% of respondents reported that they had not encountered any ethical issues related to AI tools, indicating that for some, ethical considerations are either not a concern or not applicable to their research context.

DISCUSSION

The study highlights a strong reliance on natural language processing (NLP) tools like ChatGPT and Grammarly, with 94.3% of respondents using these for writing support. This aligns with research showing the extensive and widespread use of large language models (LLMs) in research workflows, especially for tasks such as drafting, editing, and literature reviews (Bail, 2024; Gruda, 2024; Koller et al., 2024). However, the low adoption of technical tools—such as data analysis platforms (9.4%) or predictive modeling systems (18.9%) which reveals a significant gap. While NLP tools boost productivity, their use is mainly limited to basic tasks, reflecting observations that AI is often seen as a "tool in the toolbox" rather than a catalyst for innovative analysis (Shneiderman, 1983). This difference indicates that researchers tend to prefer tools that are easy to learn and provide quick benefits, a pattern also noted in studies emphasizing the "user-friendliness" of NLP tools compared to more complex AI systems (M. Lee et al., 2024). The call for new teaching methods that use AI for personalized and adaptive learning (Chadha, 2024) highlights the untapped potential of these technologies to transform core research processes beyond just writing.

Despite high awareness of AI tools (e.g., 98.1% familiarity with NLP tools), respondents reported insufficient training (M=2.43) and lack of institutional support, which hindered deeper engagement. This echoes findings by Hosseini et al. (2023), who emphasize the need for capacity-building initiatives to bridge the gap between awareness and advanced application of tools. The study's respondents overwhelmingly called for workshops (61.5%) and online tutorials (53.8%), aligning with literature advocating for structured interventions to democratize AI literacy (Fok et al., 2024; Y. Lee et al., 2024). Notably, marginalized groups—such as non-native English speakers or early-career researchers—may benefit disproportionately from such initiatives, as LLMs have been shown to "level the playing field" by reducing systemic barriers (Goyes & Skilbrei, 2024; Linxen et al., 2021). However, the underutilization of technical tools highlights the need for discipline-specific training to unlock AI's full potential in data-driven research.

Ethical concerns arose strongly, with plagiarism risks (M=4.13) and over-reliance on AI (M=3.79) being the most prominent. These results align with wider worries about LLMs threatening academic integrity through similar outputs or diminished critical thinking (Asagar, 2025; Bail, 2024; Lauer, 2023). This concern is also shown in studies on pre-service teachers who experience moral dissonance when using ChatGPT (Caling et al., 2025). However, the study shows a gap between ethical awareness and taking action to address it. For example, while

54.7% mentioned ethical concerns as a challenge, only 28.3% actively checked AI models for bias, and 17% consulted ethics committees. This reflects critiques by Wang et al. (2024) and Koller et al. (2024), who say that following general ethical guidelines (reported by 66% of respondents) is not enough without AI-specific rules. The call for clear transparency and reproducibility frameworks (Hosseini et al., 2023; Sallou et al., 2024) is especially urgent, given that respondents only have moderate confidence (M=3.75) in telling apart human- and AI-generated content. This need for clearer ethical rules is further supported by reviews that systematically examine the ethical implications of GAI in academia (Li et al., 2024).

A critical area that needs more attention is the issue of AI authorship and the accountability of AI platforms. Our results indicate moderate concern (M=3.32) about ownership of AI-generated content, but the discussion often blames students and institutions alone. This ignores the role of AI companies, whose proprietary algorithms and Terms of Service (ToS) can significantly affect academic practices. For example, users of platforms like ChatGPT or Grammarly may unintentionally give licenses to their input data, raising important questions about intellectual property and the confidentiality of unpublished research (Gendron et al., 2022; Lauer, 2023). This creates an ethical and practical dilemma where the tools used to support research could potentially compromise its ownership. Therefore, responsible AI use requires not only user education but also advocacy for increased transparency and fairer data policies from AI developers.

The perceived benefits of AI—time savings (75.5%) and efficiency (64.2%) that highlight its role as a productivity booster. However, these advantages are balanced by risks to scholarly rigor, such as hallucinations or data fabrication (Bail, 2024). Respondents, like those in earlier studies, acknowledged these dualities, with 50.9% valuing AI's accuracy but 3.8% reporting no significant impact. This tension grows in fields like medicine or law, where reproducibility and transparency are critical (Toma et al., 2023). The low engagement with open-source AI tools is essential for scrutiny and reproducibility (Sallou et al., 2024) which further complicates this balance, since reliance on commercial models risks obsolescence and opacity (Kapoor & Narayanan, 2023).

CONCLUSION

This study highlights a dynamic relationship between perceptions of AI tool value and users' practical and ethical preparedness in an academic setting. Respondents continue to show a trend toward increased awareness of AI, particularly around natural language processing (NLP)-based AI, which continues to expand; however, many users lack a deeper understanding and demonstrate minimal engagement with more advanced AI features. Although there is widespread acknowledgment of the need to incorporate AI and ML tools into academic work, practical adoption remains limited due to the lack of formal education on responsible AI use. The study also emphasizes numerous ethical issues, such as potential plagiarism, algorithmic bias, and the decline of critical thinking. These concerns are especially relevant in environments where language proficiency is limited and resources are scarce, and where institutional frameworks for AI use are either missing or underdeveloped.

To address the underuse of advanced tools (9.4%), institutions should invest in capacity-building initiatives. These could include hands-on workshops focused on responsible AI practices, such as avoiding plagiarism in AI-generated content, predictive modeling with tools like TensorFlow, and GDPR-compliant data management. Graduate curricula should be revised to include modules on AI ethics, covering bias mitigation, the responsible use of natural language processing tools like ChatGPT, and the critical evaluation of AI-generated insights. Importantly, these initiatives must also educate researchers on the often-overlooked implications of AI platform Terms of Service, advising on intellectual property risks related to uploading sensitive research data to commercial platforms. Additionally, universities' ethics committees should develop clear guidelines for attributing AI-generated content, addressing authorship concerns raised by 54.7% of participants to promote transparency and accountability among researchers and faculty. Finally, universities should advocate for greater transparency and ethical accountability from AI companies to ensure their tools support, rather than undermine, academic integrity and intellectual property rights. These efforts will foster responsible AI use and help scholars make ethical, well-informed decisions when integrating AI into their academic work.

Limitation

This study is limited by focusing on a single institution and a small sample size (n=53), which may impact how widely the findings apply. Also, relying on self-reported data might lead to response bias. Future research should incorporate mixed-methods across different institutional settings to verify and broaden these insights. It should also explore long-term AI adoption trends and compare various fields (e.g., STEM and the humanities) to better understand how AI is being integrated into academia.

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Authors' Contributions

This single author contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by both authors.

Availability of Data and Materials

The data supporting this study's findings are available upon request. They are stored in a Google Form, and access can be granted to interested parties upon request.

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