Student Integration of Artificial Intelligence (AI) Tools in Research: A Framework-Based Analysis

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***Abstract*—This mixed-methods study investigated Artificial Intelligence (AI) tool utilization among 81 student researchers in academic writing, assessing the frequency, integration extent, research performance, and adherence to ethical AI principles. The findings revealed that students predominantly use AI for language enhancement (grammar and paraphrasing) and literature review, with less engagement in complex analytical tasks. Critically, student researchers demonstrated strong self-reported ethical and human-centered AI practices, aligning with the United Nations Educational, Scientific and Cultural Organization (UNESCO) AI Competency Framework. Ethical AI adoption significantly predicted improved research performance, whereas the extent of tool integration did not. The Artificial Intelligence Utilization Scale (AIUS) Framework indicated primary engagement at Levels 3 (AI-Editing assistance) and 4 (AI-Task completion), reflecting responsible and human-supervised AI use. This study underscores the importance of fostering ethical AI literacy in effective integrity-driven academic research.**

***Keywords*—Artificial Intelligence (AI) integration, academic writing, ethical AI, United Nations Educational, Scientific and Cultural Organization (UNESCO) framework, AI utilization scale, quality education**

I. Introduction

Artificial Intelligence (AI) has rapidly emerged as a transformative force reshaping the global landscape of higher education over the past five years [1]. Its influence spans learning, teaching, and research, signifying a fundamental shift in how knowledge is produced, interpreted, and disseminated [2]. Rather than representing a mere technological enhancement, AI marks a systemic transformation that requires understanding students' use of AI not simply as tool adoption but as engagement within a changing educational ecosystem.

Worldwide, governments and institutions have heavily invested in AI-driven educational innovations. China has implemented adaptive tutoring systems such as Squirrel AI, which uses algorithms and knowledge tracing to personalize learning pathways at scale [3]. Singapore's deployment of an AI short-answer feedback assistant provides automated, standardized formative feedback, reducing teacher workload and turnaround time [4, 5]. In India, the state of Andhra Pradesh has used Microsoft AI systems to predict dropout risks, enabling targeted early interventions [6]. Georgia State University's Pounce chatbot reduced "summer melt" by 21% by answering student queries related to enrollment and financial aid [7]. Such initiatives demonstrate a global shift toward strategically embedded AI applications. The U.S. Department of Education's 2023 report further underscores this direction by promoting AI-powered tutoring, teacher support solutions, and equity-driven interventions through NSF-funded initiatives [8].

The rise of Generative AI (GenAI) accelerates this transformation. GenAI creates meaningful text, images, audio, and code using large datasets [9], extending its functions from grammar checking to content generation and feedback provision [10]. As GenAI evolves from a passive support mechanism into an "active co-creator" students increasingly engage in dynamic, dialogic interactions with AI systems. This shift affects intellectual labor, higher-order thinking skills, and academic authorship.

GenAI streamlines various stages of academic research. Tools synthesize literature by scanning databases, summarizing findings, and constructing knowledge graphs that reveal conceptual patterns and overlooked sources [11, 12]. AI enhances data analysis and visualization, enabling pattern discovery in large datasets and faster hypothesis development. In writing, AI tools improve clarity, structure, and academic tone, reducing language barriers and clerical burdens [13], while tools such as Paperpal and large language models can convert outlines into cohesive prose [14]. AI also facilitates collaboration by mapping connections between researchers and identifying overlapping interests [15]. These developments indicate that AI is now intertwined with knowledge creation, necessitating frameworks that examine how students navigate this co-creative process.

Student adoption of AI in academic contexts is widespread and increasing. Global surveys indicate that over 80% of students actively use AI for their studies. The Digital Education Council reports that 86% of students use AI, with 54% using it weekly and nearly one-fourth daily. A Chegg survey of 11,706 undergraduates across 15 countries similarly revealed that 80% use generative AI for university tasks [16]. In the Philippines, Guzman [17] found that over

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half of students use AI for academic tasks, particularly for text generation (63%), translation (58%), explaining concepts (55%), and article summarization (52%). This rapid adoption often outpaces faculty preparedness, emphasizing the need for educators not only to become AI-literate but also to guide students toward critical and ethical use [18, 19].

Students use AI for key academic tasks: locating information, summarizing texts, generating draft content, clarifying complex ideas, and suggesting research directions [16, 20]. Educators similarly employ GenAI to design lessons, provide feedback, and build rubrics, embedding AI deeper into academic practices [21]. These applications reveal AI's growing function as a cognitive partner.

AI's benefits include efficiency, automation of routine tasks, and enhanced writing support, particularly for multilingual learners. AI-powered feedback and adaptive learning systems personalize instruction, improve performance, and accommodate diverse learning needs [22, 23]. AI also democratizes academic writing by assisting those with language difficulties or learning disabilities [24]. Yet, whether these benefits contribute to "complex thinking competence" [25] and genuine learner agency [26] remains uncertain. Efficiency does not guarantee deeper learning, underscoring the need to evaluate whether AI fosters or undermines higher-order cognitive development [27].

Alongside its benefits, AI raises serious academic integrity concerns. Students and faculty worry about plagiarism, diminished critical thinking, and overreliance on AI [28]. A major integrity incident involving hidden AI prompts embedded in student papers—detected across eight countries, including the Philippines—highlights the urgent need for AI governance frameworks [29]. Concerns also persist regarding the authenticity, accuracy, and cultural relevance of AI-generated content [30]. As banning AI is neither feasible nor pedagogically sound, institutions are shifting from detection-focused approaches to strategies emphasizing AI literacy, ethical use, and assessment redesign. Alternative assessments such as oral defenses, hands-on tasks, and group outputs are increasingly recommended to ensure genuine learning [31–33]. Clear institutional guidelines are also being adopted to delineate permissible AI use [34, 35].

Despite fast AI adoption, research on its holistic impact on students remains limited. Studies on AI's effects on student well-being—digital fatigue, technostress, and loneliness—are scarce [36, 37]. Evidence on its influence on academic writing is also limited; a systematic review identified only seven empirical studies, highlighting concerns about passive learning and loss of authentic writing style despite potential writing improvements [38, 39]. Additionally, AI literacy research is fragmented and lacks a unified developmental pathway. In the Philippines, the absence of national AI policies from Commission on Higher Education (CHED) has led Higher Education Institutions to implement inconsistent regulations ranging from soft to strict policies [40], reinforcing the need for structured frameworks to guide AI integration.

Several frameworks address AI literacy. The United Nations Educational, Scientific and Cultural Organization (UNESCO) AI Competency Framework for Students identifies 12 competencies across four dimensions—human-centered mindset, ethics, AI techniques, and AI system design—organized into understanding, applying, and creating levels [41]. Other frameworks, such as the Australian Framework for GenAI in Schools [42] and multidimensional GenAI frameworks [43], emphasize responsible use and the need for explicit instruction to avoid "naïve use". AI literacy therefore requires not only technical competence but also ethical, critical, and reflective engagement with AI systems [9, 44].

This study distinguishes three core concepts: AI integration, ethical AI practices, and AI literacy. AI integration refers to how students use AI across research stages; ethical AI practices concern responsible, transparent use aligned with global guidelines; and AI literacy involves the knowledge and competencies needed to critically engage with AI in academic contexts.

To systematically analyze these dimensions, the study employs the AI Utilization Scale (AIUS) [44] alongside the UNESCO Framework. The AIUS quantifies the structural level of AI involvement across research stages, while UNESCO competencies provide an ethical and qualitative lens. Together, these frameworks allow examination of whether the extent of AI use or the quality of ethical application better predicts student performance.

Specifically, this study seeks to meet the following objectives:

1) Identify Artificial Intelligence (AI) tools and applications most frequently used by student researchers in academic research.
2) Describe how student researchers employ AI tools at each stage of the academic research writing process.
3) The extent to which AI tools are integrated across different phases of research written by student researchers.
4) Assess the overall research-class performance of student-researchers.
5) To evaluate the degree to which student researchers adopt the key principles of the UNESCO AI Competency Framework for Research Writing.
6) Determine whether the extent of AI tool integration and adoption of UNESCO-aligned ethical practices significantly predicts student-research-class performance.
7) Examine how the Artificial Intelligence Utilization Scale (AIUS) is applied in the research class in light of the observed levels of AI integration across the phases of research writing.

II. Literature Review

Artificial Intelligence (AI) refers to computer systems capable of performing tasks that require human intelligence, including learning, reasoning, and problem-solving [45]. Over the past decade, AI has shifted from basic automation to complex systems that support intelligent tutoring, academic analytics, and personalized learning environments [46]. This growth reflects institutions' increasing need to innovate pedagogical practices and enhance learning outcomes through AI-driven instructional and research support.

In the teaching–learning process, AI automates administrative tasks, assists in developing adaptive learning paths, and provides real-time feedback to optimize learner outcomes. Intelligent tutoring systems such as Carnegie Learning use dynamic content sequencing and mastery-based feedback to personalize learning at scale, showing measurable improvements in student performance [47]. AI-supported analytics also allow educators to identify at-risk learners and implement early interventions that improve academic engagement and retention [48].

AI-driven tools support students beyond classroom instruction by enhancing academic workload management and research efficiency. Language correction and style improvement platforms such as Grammarly use Natural Language Processing (NLP) and deep learning algorithms to refine clarity, tone, and coherence in academic outputs, while referencing applications like Zotero and EndNote automate citation formatting and style compliance [49]. AI-enabled tools such as ChatGPT assist with idea generation and initial structuring, QuillBot supports paraphrasing, Elicit accelerates literature synthesis, and Semantic Scholar curates high-quality academic sources using algorithmic filtering [50, 51]. As these tools become embedded in academic routines, universities have begun drafting policies that balance AI innovation with academic integrity. Institutions such as Stanford and the University of Cambridge emphasize ethical use, transparency, and accountability when incorporating AI into coursework and research [52, 53].

A. *AI in Academic Research Writing*

AI now plays a pivotal role across the entire research cycle, from conceptualization to dissemination. It aids researchers in generating research questions, synthesizing literature, managing citations, processing data, and refining manuscripts [49]. During early research stages, tools such as ChatGPT help students articulate problems and formulate researchable questions. Elicit extracts structured insights from academic papers and generates comparative tables, while Connected Papers visualizes citation networks to trace intellectual trajectories [49].

AI also assists students in outlining ideas, designing methods, coding data, and performing analytical procedures. Platforms such as SPSS and JAMOVI integrate AI-supported analytical suggestions, while formatting tools embedded in Mendeley or MS Word reduce the time spent on mechanical tasks [54].

In terms of writing quality, summarization tools simplify complex texts, grammar and style checkers enhance fluency, and tone-adjustment functions assist in achieving academic rigor. Studies report that these tools significantly improve students' writing productivity and confidence by reducing cognitive load and supporting the development of well-structured arguments [18, 46]. Recent surveys confirm the widespread adoption of AI writing tools across undergraduate and graduate populations, particularly for drafting literature reviews, organizing arguments, and finalizing manuscripts [55].

B. *Benefits and Challenges of AI Integration*

AI offers substantial benefits, including personalized feedback, enhanced access to scholarly resources, real-time academic assistance, and efficiency in repetitive tasks. These affordances help democratize learning support, particularly for large classes or students with limited faculty interaction [49, 51].

However, AI integration also poses risks. Excessive reliance on AI may impair originality, critical thinking, and student agency. Ihekweazu *et al.* [52] cautioned that outsourcing cognitive work to AI raises concerns about academic honesty and the erosion of essential research competencies. Other challenges include potential plagiarism, inaccuracies in generated content, and the temptation to accept AI responses without critical evaluation.

AI use also has emotional and psychological implications. Ou [55] found that students may experience anxiety or self-doubt when comparing their outputs with AI-generated work. Similarly, the sense of "false productivity" can lead to ineffective study habits, misunderstanding of content, and weaker internalization of learning [50].

C. *Student Use, Perceptions, and Digital Competence*

Patterns of AI use differ across disciplines, academic levels, and technological familiarity. Research shows that social science students rely heavily on AI tools for writing and literature sourcing, while STEM students tend to use AI for data analysis and visualization [54]. Digital literacy also shapes frequency and diversity of tool adoption: students with higher technological confidence explore more AI applications, whereas those from lower socioeconomic backgrounds encounter barriers due to limited access to premium AI features [56].

Gender and program differences have also emerged. Uddin [57] observed that male and technology-oriented students report higher usage rates, while female students often express more caution, citing reliability and ethical concerns. Ethical use awareness, however, remains low across student populations, with many unaware of institutional AI-use guidelines or disclosure requirements [52].

D. *Conceptual Foundations Informing AI Adoption and Use*

Rogers' Diffusion of Innovation (DOI) Theory offers a relevant lens for understanding student adoption of AI tools. DOI explains innovation uptake based on relative advantage, compatibility, complexity, trialability, and observability. Raman *et al.* [58] found that students' intention to use ChatGPT was shaped by perceived usefulness, task alignment, and ease of use. Hossain *et al.* [59] emphasized trialability and observability as crucial to ethical and effective AI adoption, while Ayanwale and Ndlovu [60] reported that complexity perceptions varied across disciplines, influencing chatbot adoption among STEM and non-STEM cohorts.

The DOI lens is highly applicable to AI adoption in Southeast Asia, where institutional policies, technological access, and cultural norms vary widely [61, 62]. These contextual differences shape how relative advantage or trialability is perceived by student researchers. In many Philippine contexts, uneven access to technology and inconsistencies in AI policies influence whether students integrate AI meaningfully or only superficially.

Complementing DOI, the Artificial Intelligence Utilization Scale (AIUS) Framework categorizes AI use across six stages of research: topic selection, literature review, data collection, data analysis, interpretation, and formatting [44]. While DOI explains why students adopt AI tools, AIUS reveals how they are applied throughout research workflows. Together, these frameworks provide a holistic perspective on student behavior, adoption drivers, and structured usage patterns.

E. *Integrated Gaps Within Existing Literature*

While global literature on AI in higher education is rapidly growing, gaps remain. There is limited localized empirical research on how Filipino student researchers use AI tools across research stages and how they reflect on their experiences. Most studies focus on tool effectiveness, ethical concerns, or theoretical implications but seldom capture student voices or analyze variations across academic programs. Furthermore, few studies integrate quantitative data on AI usage with qualitative reflections—an approach essential to understanding perceived complexity, trialability, and compatibility within the DOI framework. These contextual gaps reinforce the need for research that examines AI use within specific sociocultural and institutional environments, where issues of digital access, policy inconsistencies, and varying competencies persist [53, 56].

III. Materials and Methods

A. *Research Design*

This study employed a mixed-methods research design that specifically adopted a Sequential Explanatory approach. The design was structured in two interconnected phases rather than functioning as separate analyses, ensuring the qualitative results were directly informed by and explained the quantitative findings. The design was structured in two distinct phases, quantitative and qualitative, wherein the qualitative phase served to elaborate on and deepen the interpretation of the quantitative findings.

In the quantitative phase (Phase I), a descriptive-correlational research design was utilized to (1) identify the Artificial Intelligence (AI) tools and applications most frequently used by student researchers, (2) describe the specific ways in which AI tools are employed across various stages of academic research writing, (3) assess student researchers' performance in their research class, and (4) examine predictive relationships between the extent of AI integration, adoption of the key principles of AI (aligned with the UNESCO AI Competency Framework), and research performance. This phase specifically answered Research Questions 1 to 6. This phase involved the administration of structured survey questionnaires, and the data were analyzed using descriptive statistics, t-tests, and multiple regression analysis.

Following the analysis and interpretation of the quantitative data, a qualitative phase (Phase II) was conducted to further explore and contextualize the findings. Crucially, this phase did not involve the collection of primary qualitative data (such as interviews or focus groups). Analytical depth was achieved through document analysis via a structured, deductive content analysis of the quantitative usage data. This process functioned as the primary coding mechanism: the reported percentages of AI integration (from the quantitative survey) were systematically and deductively mapped to the Artificial Intelligence Utilization Scale (AIUS) predefined conceptual levels. The purpose of this qualitative mapping was to determine how closely student researchers' actual practices align with the levels and principles outlined in AIUS, thereby offering a deeper understanding of the nature and ethical scope of AI use in academic research.

This sequential explanatory design, by linking quantitative usage patterns to a conceptual framework through deductive mapping, enabled a comprehensive investigation of measurable trends and the conceptual alignment of these practices with the established competency frameworks.

B. *Respondents of the Study*

A total of 81 graduating students ($N = 81$) participated in the study. Participants were purposively selected from two specific academic programs: the Bachelor of Elementary Childhood Education (BECED) and the Bachelor of Secondary Education Major in Values Education (BSED-VE). This targeted sample size, while providing significant contextual depth for framework analysis, inherently limits the generalizability of the findings to a broader student population or other academic disciplines.

The selection was deliberately non-random because these students were enrolled in a research course under the instruction of a professor who actively integrated Artificial Intelligence (AI) tools. Their direct exposure to structured, AI-supported instruction provides a highly controlled and relevant basis for assessing AI use in research writing, thereby strengthening the study's internal validity regarding the specific frameworks examined.

This purposeful selection also aligned with the university's current transition toward institutional AI integration. At the time of the study, the university was in the early stages of adopting AI into the curriculum and had recently approved formal guidelines, including the Artificial Intelligence Utilization Scale (AIUS). The professors of these research classes implemented the AIUS as a guiding framework for students' responsible and strategic use of AI throughout the research process. The application of the AIUS offered a meaningful context to examine how student researchers integrated AI tools across different research writing phases and how such practices align with institutional expectations and ethical standards.

Respondents' engagement in undergraduate thesis writing and their familiarity with AI tools positioned them to reflect on their AI adoption behavior. Within this specific cohort, their participation enabled the study to explore potential variations in AI use based on academic programs and sex, adding valuable detail to the analysis.

C. *Instruments of the Study*

This study utilized three research instruments to ensure a systematic alignment between the study's objectives and the different dimensions of student researchers' use of Artificial Intelligence (AI) in academic research writing. The first instrument, the Student AI Utilization Patterns Questionnaire, was adapted from Walter [44]. It was designed to measure three key dimensions: (1) the frequency of use of various AI tools and applications in academic research; (2) the specific ways in which student researchers employed these tools across the stages of the research writing process; and (3) the extent to which AI was integrated into research activities. To ensure content validity, the instrument was reviewed by a panel of experts in AI-assisted research and educational measurements. Subsequently, a pilot test was conducted with a separate group of students to assess reliability, demonstrating high internal consistency with a Cronbach's alpha coefficient of 0.921. This instrument addressed Research Questions 1, 2, and 3, enabling the study to identify AI usage patterns and behavioral integration across the research workflow.

The second instrument focused on measuring the adoption of the key ethical and human-centered principles outlined in the UNESCO AI Competency Framework for Research Writing, as perceived by student researchers. The questionnaire was developed based on five core dimensions of the framework: (1) fostering a critical approach to AI, (2) prioritizing human-centered interaction with AI, (3) encouraging environmentally sustainable AI, (4) promoting inclusivity in AI competency development, and (5) building core AI competencies for lifelong learning. The tool was subjected to pilot testing with 35 graduating students enrolled in a research writing course under the same professor who facilitated AI integration; however, these pilot participants were excluded from the main study. The instrument demonstrated excellent reliability across all dimensions, with Cronbach's alpha values ranging from 0.749 to 0.927, and overall internal consistency rated at 0.952. This instrument addressed Research Question 5 and contributed to Research Question 6 by providing data on students' ethical and principled engagement with AI tools.

The third instrument consisted of the students' final grades in their research class, which served as a direct indicator of academic performance outcomes. This addressed Research Question 4 and supported Research Question 6 by allowing the determination of whether AI integration and ethical AI practices significantly influenced student performance.

Together, the three instruments ensured a complete and coherent analysis of the study variables: from behavioral usage patterns and ethical considerations to actual performance outcomes. Their complementary roles strengthened the clarity of the research stages within the sequential explanatory design, highlighting the progression from AI usage to ethical reflection to measurable academic results.

D. Data Collection, Analysis, and Statistical Treatment

Data collection was conducted in two phases, corresponding to a sequential explanatory mixed methods design. In the quantitative phase, validated survey instruments were administered to 81 purposively selected graduating students from the Bachelor of Elementary Childhood Education (BECED) and Bachelor of Secondary Education major in Values Education (BSED-VE) programs. The respondents were enrolled in a research class under a professor who actively integrated Artificial Intelligence (AI) into teaching and learning. This unique instructional context, combined with the university's recent adoption of institutional AI guidelines, including the Artificial Intelligence Utilization Scale (AIUS) as part of its official policy, has provided a meaningful backdrop for examining students' AI usage patterns.

The survey responses were encoded and subjected to statistical analyses using statistical software. Descriptive statistics (frequency, percentage, mean, and standard deviation) were used to summarize the data on frequently used AI tools, their specific applications across research phases, and perceived adoption of the UNESCO AI Competency Framework dimensions. Independent sample t-tests were conducted to compare the extent of AI integration by gender and academic program. Multiple regression analysis was used to determine the predictive power of AI integration and ethical AI practices on students' research class performance. The significance level was set at $\alpha = 0.05$ for all inferential tests.

Following the quantitative analysis, a qualitative phase was undertaken through document analysis, specifically to map the extent of AI use across research writing phases with reference to the Artificial Intelligence Utilization Scale (AIUS) framework. This analysis enabled the researchers to assess how student-researchers' practices aligned with AIUS levels (from idea generation to full AI collaboration) based on the percentage of AI integration reported in each research stage. Patterns were examined to determine whether students used AI responsibly in accordance with the intended learning outcomes and ethical standards outlined in the university's AI guidelines.

The integration of both quantitative and qualitative data allowed for a comprehensive interpretation of student-researchers' AI use, reflecting not only behavioral patterns and performance outcomes but also the ethical, pedagogical, and institutional contexts in which AI tools were applied in academic research writing.

IV. Results and Discussion

A. Artificial Intelligence (AI) Tools and Applications Most Frequently Used by Student-Researchers in Academic Research

In recent years, the academic landscape has witnessed a growing reliance on Artificial Intelligence (AI) tools to support research writing and scholarly productivity. In particular, student researchers are increasingly adopting a wide range of AI applications, such as grammar checkers, paraphrasing tools, content generators, and citation management, to streamline the complex processes involved in academic research. The findings show that students utilize a variety of AI tools that support different stages of the academic research writing process. Identifying the tools that are most frequently used highlights the specific areas of research work where students rely on AI assistance and reveals patterns in their integration of technology into scholarly tasks. This focus on actual usage behavior provides a clearer understanding of how students incorporate AI into research-related activities within the academic context.

This section explores the dominant AI applications utilized in academic research, highlighting the patterns of adoption that reflect the evolving learning behaviors in the digital age.

The data presented in Table 1 highlights the prevalence and distribution of Artificial Intelligence (AI) tools used by student researchers in academic research. Notably, Scispace emerged as the most frequently used AI application, with 95.83% of respondents indicating its use. This reflects a strong preference for tools that facilitate the comprehension and synthesis of academic literature, as Scispace is primarily designed to simplify technical content and to extract key insights from scholarly articles.

Table 1. Most frequently used AI Tools by student-researchers

AI Tools and Apps	Frequency	Percentage	Rank
ChatGPT/OpenAI	63	87.50%	2.5
Consensus	14	19.44%	6
Grammarly	63	87.50%	2.5
Microsoft Co-pilot	10	13.89%	7
Quillbot	44	61.11%	4
Scispace	69	95.83%	1
Scite.ai	4	5.56%	9
Online Statistics Calculator	21	29.17%	5
Avidnote	1	1.39%	10
Napkin	5	6.94%	8

Both ChatGPT/OpenAI and Grammarly followed closely, as reported by 87.50% of the students. These tools serve distinct yet complementary purposes. ChatGPT is a generative AI model for idea development, drafting, language support, grammar correction, and writing enhancement. Their high usage suggests that student researchers depend heavily on AI to improve the linguistic quality and coherence of their academic writings.

Quillbot, a paraphrasing tool, was used by 61.11% of the respondents, indicating the importance placed on content rephrasing and text variation, possibly as a strategy to avoid plagiarism or improve readability. Tools for statistical support, such as Online Statistics Calculator, were moderately used (29.17%), pointing to a more limited engagement with AI in data analysis and quantitative tasks.

Less frequently used tools included Consensus (19.44%), Microsoft Co-pilot (13.89%), Napkin (6.94%), Scite.ai (5.56%), and Avidnote (1.39%). The lower frequency of these tools may be attributed to limited awareness, access issues, or a lack of familiarity with specific functionalities. The minimal use of citation analysis platforms (e.g., Scite.ai) and academic note-taking apps (e.g., Avidnote) suggests that students may underutilize AI during critical stages of literature evaluation and research organization.

The results indicate that student-researchers predominantly use AI tools designed for text generation, grammar refinement, paraphrasing, citation formatting, and idea development. Tools such as ChatGPT, Grammarly, and QuillBot were consistently ranked highest in frequency of use. This pattern shows that students rely more on language- and writing-specific AI applications rather than tools for data management, data visualization, or advanced analytics, which were reported as least frequently used. These findings suggest that AI integration in academic research among the respondents is currently concentrated on improving written output and addressing challenges in academic writing, particularly during the idea formulation and manuscript preparation stages, rather than supporting statistical or methodological components of the research process.

Overall, the findings indicate that students strategically employ AI tools in areas where they perceive the greatest need for support, particularly in refining written language, improving clarity, and organizing content**.** Their lower utilization of AI for data analysis, methodological decision-making, and advanced research tasks reflects the current stage of AI integration in academic settings, wherein students remain more confident in maintaining control over core research processes such as data interpretation and argument construction. This usage pattern aligns with the study's context, where AI adoption is emerging and primarily utilized as a supplementary aid to improve writing quality, rather than as a primary driver of research generation or decision-making.

B. Application of AI Tools Across Stages of Academic Research Writing

The data presented in Table 2 highlights how student researchers employ artificial intelligence tools across various stages of academic research. The highest frequency of use was observed for tasks related to language enhancement. Writing assistance and grammar checking ranked first, with 81.94% of respondents indicating frequent use, suggesting that students highly value AI in improving the clarity, coherence, and grammatical accuracy of their work. This is followed by paraphrasing, summarization, and content enhancement (68.06%), and literature review and research paper discovery (66.67%), indicating that AI tools are instrumental in helping students refine text and efficiently scan academic sources.

Table 2. AI utilization across research writing stages by students

Stages of Academic Research Writing	Frequency	Percentage	Rank
Research Topic Generation and Idea Development	36	50.00%	5
Literature Review and Research Paper Discovery	48	66.67%	3
Data Collection and Analysis	16	22.22%	8
Writing Assistance and Grammar Checking	59	81.94%	1
Citation and Reference Management	35	48.61%	6
Paraphrasing, Summarization, and Content Enhancement	49	68.06%	2
Plagiarism Detection and Similarity Checking	39	54.17%	4
Content Structuring and Formatting	14	19.44%	9.5
AI for Statistical Analysis	14	19.44%	9.5
Research Paper Writing and Drafting	11	15.28%	11
Abstract and Executive Summary Writing	7	9.72%	13
Proofreading, Editing, and Revisions	27	37.50%	7
Visualization and Data Presentation	9	12.50%	12

Moderate levels of AI utilization were found in stages such as plagiarism detection and similarity checking (54.17%), and research topic generation and idea development (50.00%). This pattern suggests that while students are beginning to explore AI for conceptual development and maintaining academic integrity, these areas are still not as consistently supported by AI as basic writing tasks.

On the other hand, AI use significantly declines in the more complex technical aspects of the research process. Only 22.22% of students reported using AI for data collection and analysis, and a mere 19.44% utilized AI for either statistical analysis or content structuring and formatting. Tasks such as research paper writing and drafting (15.28%), visualization and data presentation (12.50%), and abstract and executive summary writing (9.72%) fall at the lowest end of the spectrum. This declining trend may indicate limited student confidence or proficiency in applying AI to higher-order analytical and integrative tasks. This also suggests that students tend to rely more on AI for surface-level support than for tasks that require deeper methodological and critical thinking.

Overall, the data points to a tendency among student researchers to use AI primarily for polishing text and organizing information rather than for content generation or data-driven decision-making. This reveals a critical opportunity for institutions to provide training on how AI can be more effectively applied to the full research cycle, particularly in the analytical and synthesis stages, to maximize its academic value and deepen students' research competence.

C. Extent of AI Integration Across Research Writing Phases by Student-Researchers

The pattern of mean scores in Table 3 shows that student researchers deploy artificial-intelligence tools principally for language–oriented and integrity-oriented tasks, while engagement falls off for methodology-heavy activities. The highest means, 3.03 ± 1.27, is recorded for Writing Assistance and Grammar Checking, closely followed by Plagiarism Detection and Similarity Checking (3.10 ± 1.27), Paraphrasing, Summarization, and Content Enhancement (2.83 ± 1.13), and Citation and Reference Management (2.78 ± 1.35). All four lie in the 41–60% usage band, indicating that AI is routinely—but not ubiquitously—embedded in stages that polish prose, paraphrase text, or safeguard originality.

Table 3. Extent of AI use in academic research writing

Extent of AI Use	Ave Rating	SD	Description
Research Topic Generation and Idea Development	1.93	1.17	21–40%
Literature Review and Research Paper Discovery	2.93	1.41	41–60%
Data Collection and Analysis	1.89	1.17	21–40%
Writing Assistance and Grammar Checking	3.03	1.27	41–60%
Citation and Reference Management	2.78	1.35	41–60%
Paraphrasing, Summarization, and Content Enhancement	2.83	1.13	41–60%
Plagiarism Detection and Similarity Checking	3.10	1.27	41–60%
Content Structuring and Formatting	2.26	1.21	21–40%
AI for Statistical Analysis	2.22	1.36	21–40%
Research Paper Writing and Drafting	2.13	1.21	21–40%
Abstract and Executive Summary Writing	1.97	1.14	21–40%
Proofreading, Editing, and Revisions	2.31	1.38	21–40%
Visualization and Data Presentation	2.06	1.17	21–40%
Overall	**2.42**	**1.25**	**21–40%**

In contrast, tasks that require deeper analytical engagement, Data Collection and Analysis (1.89 ± 1.17), AI for Statistical Analysis (2.22 ± 1.36), and Visualization and Data Presentation (2.06 ± 1.17)—fall in the 21–40 % range. Similarly, low scores appeared for structural activities such as Content Structuring and Formatting (2.26 ± 1.21) and Research Paper Writing and Drafting (2.13 ± 1.21). These findings suggest either limited awareness of advanced AI capabilities or reluctance to rely on AI for tasks perceived as more cognitively demanding.

Standard deviations cluster between 1.13 and 1.41, signalling moderate to high dispersion and implying heterogeneous adoption patterns across the student cohort. Some individuals integrate AI extensively throughout the workflow, whereas others use it sparingly.

The overall mean of 2.42 ± 1.25 confirms a "moderate" extent of AI use (21–40 %) when all stages are considered together. From an instructional standpoint, the data highlights the need to broaden AI literacy beyond surface-level language support to encompass data analysis, statistical inference, and content structuring, thereby promoting a more balanced and methodologically robust AI application in academic research.

D. Research-Class Performance of Student-Researchers

Understanding the academic performance of student researchers is vital for evaluating the outcomes of pedagogical innovations such as the integration of Artificial Intelligence (AI) tools in research writing. Performance in the research class serves as a key indicator of how well students are able to apply their research skills, synthesize knowledge, and produce scholarly output under guided instruction. In this study, performance was assessed through final grades, reflecting students' ability to research while engaging with AI-supported tools and frameworks. These performance data provide a baseline for interpreting the impact of AI tool integration and the adoption of AI competency principles on students' research and learning outcomes.

The academic performance of student researchers in their research classes, as shown in Table 4, revealed a generally high level of achievement. Based on the recorded final grades, the scores ranged from 91 to 99, with an average of 95. This average falls within the "Excellent" qualitative category based on the institution's grading standards. Out of 72 students, a significant majority (57%) received grades between 95 and 99, indicating exceptional performance. Specifically, 18 students (25%) achieved a near-perfect score of 99, while another 14 students (19.44%) earned a grade of 95. Additionally, eight students scored 96, and a smaller subset achieved scores of 97 and 98, respectively.

Table 4. Academic performance distribution of student-researchers in the research class

Performance in Research	Frequency	Percentage
91 (Very Good)	5	6.94%
92 (Very Good)	18	25.00%
93 (Very Good)	0	0.00%
94 (Very Good)	1	1.39%
95 (Excellent)	14	19.44%
96 (Excellent)	8	11.11%
97 (Excellent)	3	4.17%
98 (Excellent)	5	6.94%
99 (Excellent)	18	25.00%
Total	**72**	**100.00%**
Average Score	**95**	-
Overall Performance Description	**Excellent**	-

Meanwhile, 25% of the students scored 92, the most frequent score in the "Very Good" range, suggesting that while most students performed at the highest level, a smaller group still demonstrated strong, albeit slightly lower, academic outcomes. Notably, none of the students received a score below 91, and only one student scored 94, reinforcing the overall trend of high academic performance in the cohort.

The consistency of these exceptionally high scores across the group should be contextualized. These grades are standard to the state university and stipulated in the students' manual. Furthermore, the high performance may be partially attributed to the structured instructional approaches, including the active integration of AI tools supported by the Artificial Intelligence Utilization Scale (AIUS) framework. These tools are likely to enhance students' research efficiency, organization, and writing quality. However, while performance outcomes are impressive, the clustering of grades in the upper range may also warrant further investigation into the grading criteria and assessment practices used, particularly in the context in which AI-assisted outputs may influence perceptions of student capability.

Overall, the findings suggest that students enrolled in a research class that incorporated AI-assisted learning guided by the AIUS framework could perform at an excellent academic level. This reinforces the potential of well-structured AI integration to support and elevate student researchers' academic performance in higher-education settings.

E. Extent of Ethical and Reflective AI Use Among Student-Researchers Based on the UNESCO AI Competency Framework

Table 5 captures the student researchers' self-reported commitments to critical and ethical engagement with AI. Mean ratings cluster narrowly between 3.31 and 3.42 on a four-point Likert scale, yielding an overall average of 3.36 (SD = 0.70). As all items mean exceeded 3.30, the cohort collectively "agreed" that they should apply reflective judgment when deploying AI in research writing.

Table 5. Fostering a critical approach to AI

Indicators	Ave Rating	SD	Description
I consciously examine the accuracy and trustworthiness of AI-generated content before integrating it into my research work.	3.38	0.72	Agree
I reflect on the ethical implications (e.g., authorship, bias, environmental impact) of using AI tools in writing and presenting my research.	3.35	0.67	Agree
I make deliberate decisions on whether or not AI tools should be used in specific parts of the research process based on their appropriateness and limitations.	3.31	0.70	Agree
I seek to understand how AI tools influence human agency, equity, and sustainability when applied in academic research settings.	3.38	0.72	Agree
I recognize that AI is not a one-size-fits-all solution and use it only when it supports deeper inquiry and meaningful contribution to my research objectives.	3.42	0.69	Agree
Overall	**3.36**	**0.70**	**Agree**

Note: Legend: SD-Standard Deviation

The strongest endorsement ($M = 3.42$, SD = 0.69) concerns recognizing that AI is not a one-size-fits-all solution and limits its use to contexts that deepen inquiry. Closely aligned items were used to verify the accuracy and trustworthiness of AI outputs and probe AI's broader impacts of AI on agency, equity, and sustainability (both $M = 3.38$). These high scores suggest a pronounced awareness that AI must augment, not replace, scholarly rigor and human oversight.

Slightly lower, although still affirmative, was the item on making deliberate decisions about where AI is appropriate ($M = 3.31$, SD = 0.70). Although students generally agree, this marginal dip may indicate uncertainty when judging AI's limitations at specific methodological stages.

Standard deviations ranging from 0.67 to 0.72 indicate modest dispersion, implying a relatively homogeneous stance across the sample; most respondents endorsed reflective practice rather than a small subset driving the mean upward. This consensus reinforces the conclusion that critical engagement with AI is becoming normative.

Taken together, these results portray a student body that does not uncritically embrace AI. Instead, they routinely interrogate accuracy, weigh ethical ramifications, and tailor AI use according to the research objectives. From a pedagogical perspective, these findings affirm the value of embedding AI literacy and ethics modules within research curricula and highlight the need for concrete decision-making frameworks to help students determine the appropriateness of AI at each research phase.

The findings in Table 6 highlight the extent to which student researchers prioritize a human-centered approach in their use of Artificial Intelligence (AI) tools during the research process. With an overall mean score of 3.49 and a Standard Deviation (SD) of 0.70, the data suggest a consistently high level of agreement among students regarding the importance of maintaining human agency and ethical awareness when integrating AI into academic work.

Table 6. Prioritizing human-centered interaction with AI

Indicators	Ave Rating	SD	Description
I ensure that AI tools support my learning and thinking, rather than replace my own ideas and critical analysis in writing research.	3.43	0.82	Agree
I maintain personal accountability and decision-making over my research outputs, even when using AI-assisted tools.	3.51	0.67	Strongly Agree
I use AI tools in ways that respect privacy, uphold ethical standards, and promote fairness in the research process.	3.51	0.67	Strongly Agree
I understand the value of human creativity and judgment, and I avoid over-relying on AI in developing and expressing my research ideas.	3.51	0.65	Strongly Agree
I reflect on how AI tools affect my autonomy and strive to use them in ways that enhance, not diminish, my role as a researcher.	3.49	0.71	Agree
Overall	**3.49**	**0.70**	**Agree**

Note: Legend: SD-Standard Deviation

The highest-rated indicators, each with a mean of 3.51, reflected students' strong commitment to three key principles: maintaining personal accountability for AI-assisted outputs, ensuring the ethical and fair use of AI tools that respect privacy, and valuing human creativity and judgment over reliance on automation. These responses suggest that students understand the importance of ethical integrity and original thinking even when leveraging technological support.

Although still strongly endorsed, slightly lower average scores were recorded for the indicators addressing the role of AI in supporting critical thinking ($M = 3.43$, SD = 0.82) and reflection on how AI impacts personal autonomy ($M = 3.49$, SD = 0.71). The relatively higher variability in the responses to these two indicators may indicate that some students still navigate how to use AI meaningfully without compromising their independent thinking and authorship.

Overall, the results affirm that student researchers are not only aware of the ethical responsibilities associated with AI use but are also actively striving to use AI in ways that enhance, rather than diminish, their learning, creativity, and role as knowledge producers. The strong agreement across all indicators provides evidence of a reflective and value-driven approach to AI integration.

The results presented in Table 7 reflect student–researcher perspectives on the environmental sustainability of Artificial Intelligence (AI) use in academic research. With an overall average rating of 3.31 and a Standard Deviation (SD) of 0.72, the findings indicate a consensus among respondents, who agree with the importance of adopting environmentally conscious practices when using AI tools in research writing.

Table 7. Encouraging environmentally sustainable AI

Indicators	Ave Rating	SD	Description
I am aware that training and using AI tools in research writing can contribute to carbon emissions and environmental degradation. →This means understanding that the computing power behind AI tools consumes energy and can have negative effects on the environment.	3.22	0.77	Agree
I reflect on the environmental impact of using AI tools and consider sustainability when deciding to use them in my research work. →This encourages you to think critically about when and how often you use AI tools, keeping in mind their environmental cost.	3.38	0.70	Agree
I seek information about how AI systems consume energy and consider these factors when choosing which AI tools to use. → This means taking the initiative to learn about the energy consumption and sustainability practices of different AI platforms.	3.29	0.70	Agree
I believe that AI tools used in academic research should be designed and implemented with environmental sustainability in mind. → This reflects your support for using eco-friendly AI technologies and promoting their development in educational and research settings.	3.33	0.75	Agree
I adopt responsible practices in using AI by balancing its benefits in research with its potential environmental consequences. → This involves using AI tools only when necessary and being mindful of their environmental impact while conducting research.	3.33	0.69	Agree
Overall	**3.31**	**0.72**	**Agree**

Note: Legend: SD-Standard Deviation

Across all five indicators, the students consistently agreed with statements related to environmental awareness and responsibility. The highest-rated item (M = 3.38, SD = 0.70) showed that many student researchers began to reflect on the environmental consequences of AI usage, particularly when deciding how and when to employ such tools in their academic work. Similarly, a mean score of 3.33 was observed for two key indicators: support for the environmentally sustainable design and implementation of AI technologies and the practice of balancing AI's research benefits against its ecological costs. These responses suggest an emerging ethical orientation among students toward minimizing their carbon footprint while utilizing advanced technologies.

The indicator with the lowest mean score (M = 3.22, SD = 0.77) relates to the technical awareness that AI training and usage can contribute to carbon emissions. This slightly lower score, along with its relatively higher standard deviation, suggests that while many students are aware of this issue generally, a significant proportion may still lack a full understanding of the technical and energy-intensive processes behind large-scale AI operations. Nonetheless, the mean scores for all items fall within the "Agree" range, demonstrating that respondents generally recognize the environmental implications of AI and are open to making informed, sustainable choices.

In summary, the data confirm that student researchers are developing a conscientious attitude toward the ecological dimensions of AI use, demonstrating a willingness to incorporate sustainability considerations into their academic practices. This student readiness presents a direct, leveraged opportunity for institutions to integrate AI literacy into their broader educational sustainability goals. By moving beyond theoretical awareness to include explicit curriculum components on selecting energy-efficient AI tools and implementing responsible computing practices, institutions can effectively fulfill their mandates for environmental stewardship and green technology adoption. This trend underscores the importance of formally embedding environmental literacy within digital and AI competency frameworks in higher education.

The findings presented in Table 8 highlight student–researchers' perceptions and practices regarding inclusivity in the development and use of Artificial Intelligence (AI) tools in academic research. With an overall average rating of 3.43 (SD = 0.67), the data suggest consistent agreement among respondents on the importance of promoting equitable access, representation, and fairness in the AI tools they engage with during the research-writing process.

Table 8. Promoting inclusivity in AI competency development

Indicators	Ave Rating	SD	Description
I consider whether the AI tools I use in research writing are accessible and inclusive to people from diverse backgrounds.	3.43	0.62	Agree
I recognize and reflect on possible biases in AI-generated content, especially those related to gender, culture, or socio-economic status.	3.43	0.67	Agree
I support the use of AI tools that are designed to accommodate users with disabilities or diverse linguistic needs in research settings.	3.46	0.69	Agree
I believe that affordable, open-source, and easy-to-access AI tools should be prioritized in research education.	3.40	0.73	Agree
I am mindful of how the design and application of AI tools in my research may affect people from underrepresented or marginalized groups.	3.44	0.65	Agree
Overall	**3.43**	**0.67**	**Agree**

Note: Legend: SD-Standard Deviation

Among the specific indicators, the highest mean score (M = 3.46, SD = 0.69) corresponds to support for AI tools designed to accommodate users with disabilities and diverse linguistic needs. This finding suggests that student researchers value inclusive design features that broaden their participation in research, especially for individuals who might otherwise face technological barriers. Close in rating is the consideration of accessibility across diverse backgrounds (M = 3.43, SD = 0.62) and reflections on potential biases in AI-generated content (M = 3.43, SD = 0.67), indicating growing awareness of how embedded algorithmic biases could reinforce social inequalities.

The respondents also acknowledged the significance of affordability and openness in AI platforms, as reflected in their agreement with the statement that open-source, easy-to-access tools should be prioritized in research education (M = 3.40, SD = 0.73). Furthermore, the item on being mindful of how AI design may impact marginalized groups (M = 3.44, SD = 0.65) reinforces the idea that students are not only aware of potential harm but are also motivated to use AI responsibly and ethically.

Overall, the pattern of responses points to a maturing ethical consciousness among student researchers. They are increasingly attuned to issues of inclusivity, accessibility, and social justice as they incorporate AI into their scholarly activities. These results emphasize the importance of embedding principles of diversity and equity in AI education, policy, and practice within academic institutions.

The results in Table 9 illustrate the extent to which student researchers are building foundational Artificial Intelligence (AI) competencies that contribute to their development as lifelong learners. An overall mean score of 3.35 (SD = 0.71) indicates that respondents generally *agree* that they are engaging with AI tools in ways that foster growth in knowledge, ethics, creativity, and responsible application.

Table 9. Building core AI competencies for lifelong learning

Indicators	Ave Rating	SD	Description
I continuously explore how AI tools work and how they can be adapted to support new research tasks and contexts.	3.36	0.74	Agree
I understand and consider ethical issues such as bias, privacy, and accountability when using AI in my research writing.	3.53	0.67	Strongly Agree
I can identify and apply basic AI concepts—like data use, algorithms, and model limitations—when working on research tasks.	3.21	0.71	Agree
I take the initiative to improve my skills in using AI tools responsibly to support my long-term academic and professional goals.	3.31	0.70	Agree
I use AI in ways that promote creativity, solve problems, and connect with real-world challenges in research writing.	3.33	0.71	Agree
Overall	**3.35**	**0.71**	**Agree**

Note: Legend: SD-Standard Deviation

Notably, the highest-rated item, "I understand and consider ethical issues such as bias, privacy, and accountability when using AI in my research writing," received a mean of 3.53 (SD = 0.67), suggesting strong agreement and high self-awareness in navigating the ethical landscape of AI use. This finding underscores that students are not merely passive users of AI but are developing the moral reasoning necessary for its responsible integration in scholarly work.

The remaining indicators received ratings within the 3.21 to 3.36 range, signifying a consistent affirmation of essential AI competencies. For instance, student researchers agreed that they actively explore how AI tools function and adapt them to new tasks (M = 3.36, SD = 0.74) and that they apply basic AI concepts such as data use, algorithms, and model limitations in research settings (M = 3.21, SD = 0.71). These findings reflect an emergent cognitive engagement with the mechanics and implications of AI technologies, suggesting growing fluency with the tools themselves and the broader systems they represent.

Moreover, students indicated initiatives to improve their AI skills for long-term academic and professional success (M = 3.31, SD = 0.70) and reported using AI to enhance creativity and address real-world challenges (M = 3.33, SD = 0.71). These responses suggest that AI is increasingly viewed not only as a tool for efficiency but also as a means of innovation and problem-solving in academic contexts.

Collectively, the pattern of responses demonstrates that student researchers cultivate well-rounded, future-oriented AI literacy. Their competencies include technical understanding, ethical mindfulness, skill development, and creativity, all of which are critical elements in fostering adaptable and socially responsible researchers in an AI-augmented academic landscape.

The data presented in Table 10 provides a synthesized overview of student-researchers' self-reported adherence to the five key dimensions of the UNESCO AI Competency Framework as applied to academic research writing. The overall mean score of 3.39 (SD = 0.70) indicated general agreement among respondents, reflecting a positive level of adoption and internalization of responsible, ethical, and reflective AI use in the research process.

Table 10. Summary of the UNESCO AI competency framework for research writing

Indicators	Ave Rating	SD	Description
Fostering a Critical Approach to AI	3.36	0.70	Agree
Prioritizing Human-Centered Interaction with AI	3.49	0.70	Agree
Encouraging Environmentally Sustainable AI	3.31	0.72	Agree
Promoting Inclusivity in AI Competency Development	3.43	0.67	Agree
Building Core AI Competencies for Lifelong Learning	3.35	0.71	Agree
Overall	**3.39**	**0.70**	**Agree**

Note: Legend: SD-Standard Deviation

Among the five dimensions, "Prioritizing Human-Centered Interaction with AI" obtained the highest average rating (M = 3.49, SD = 0.70), highlighting that student researchers are particularly conscious of maintaining their agency, critical thinking, and ethical responsibility when engaging with AI tools. This suggests that learners value the human role in the research process and use AI primarily as a complement to, rather than a replacement for, intellectual effort and creativity.

Following closely is "Promoting Inclusivity in AI Competency Development" (M = 3.43, SD = 0.67), which reflects an awareness of the need for fairness, accessibility, and sensitivity to bias in AI usage. This finding indicates that students consider how AI tools accommodate diverse users and are attentive to social equity in their technological choices.

The dimensions “Fostering a Critical Approach to AI” (*M* = 3.36), “Building Core AI Competencies for Lifelong Learning” (*M* = 3.35), and “Encouraging Environmentally Sustainable AI” (*M* = 3.31) were all rated positively, though at slightly lower levels. These scores still suggest meaningful engagement with reflective practices, including the critical evaluation of AI outputs, concern for the environmental footprint of AI usage, and commitment to continuous learning and ethical improvement.

Taken together, the findings indicate that student researchers not only integrate AI tools into their academic workflows but also develop a holistic awareness of the broader implications of AI in education and research. Their responses align with the principles of responsible AI use outlined by UNESCO, suggesting a foundational readiness to participate in an evolving academic landscape shaped by artificial intelligence.

Table 11. Comparison of the extent of AI use among student-researchers by gender and academic program

Variables Compared	*t*	sig-value	Decision	Interpretation
Extent of AI Use and Gender	–0.006	0.995	Do not reject Ho	There is no significant difference in the Extent of AI Use of Male and Female student-researchers
Extent of AI Use and Academic Program	1.673	0.099	Do not reject Ho	There is no significant difference in the Extent of AI Use of BSED and BECED student-researchers

Note: Legend: *t*-test

The results presented in Table 11 provide insight into whether the extent of Artificial Intelligence (AI) utilization among student researchers differs significantly based on gender and academic programs. Statistical analysis using independent-samples *t*-tests revealed no significant difference in AI usage between male and female students, as indicated by a *t*-value of –0.006 and significance level (*p*) of 0.995. This extremely high *p*-value strongly suggests that gender did not play a determining role in the extent of AI tool usage among respondents. The negligible *t*-value further reinforces that the mean scores between the two groups are virtually identical, highlighting a consistent pattern of AI engagement regardless of gender.

Similarly, a comparison between students from the Bachelor of Secondary Education (BSED) and the Bachelor of Early Childhood Education (BECED) programs resulted in a *t*-value of 1.673 and a *p*-value of 0.099. Although BSED students demonstrated slightly higher usage rates, the results did not reach the standard level of statistical significance. Thus, it can be inferred that students’ academic programs do not significantly influence the extent of their AI integration in research-writing tasks. However, the *p*-value, which borders marginal significance, suggests the possibility of a small emerging trend that may become more pronounced with larger sample sizes or additional program comparisons.

Overall, the findings point to a generally equitable pattern of AI utilization among student researchers across gender and academic backgrounds. This uniformity implies that access to AI tools and their adoption in research practices are not limited by demographic or academic segmentation, supporting the notion of inclusive AI integration in higher education settings.

F. Influence of AI Integration and Ethical Practices on Student-Researchers’ Performance in Research Class

The multiple regression analysis, summarized in Table 12, was performed to examine the predictive relationship between the extent of AI tool integration and the adoption of ethical and reflective practices on student researchers’ performance in their research class. Before interpretation, the model was assessed for multicollinearity, yielding Variance Inflation Factor (VIF) values well below the critical threshold of 10, thus confirming that the two independent variables were suitably distinct for inclusion in the model.

Table 12. Multiple regression analysis on the influence of AI integration and the adoption of key principles in the UNESCO AI competency framework on research performance

Item Category	Independent Variable	Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.	Interpretation
		B	Std. Error	Beta			
Regression Results	Extent of Integration of AI Tools	–0.150	0.375	–0.047	–0.399	0.691	Not significant
Regression Results	Adoption of the key principles in the UNESCO AI Competency Framework (in research performance)	1.288	0.618	0.245	2.083	0.041	Significant
Model Summary	-	*r* = 0.239446	R-squared = 0.0573342	*F*-value = 4.257491	*p*-value = 0.0427877	alpha = 0.05	-

Note: Dependent Variable: Research Performance; Legend: B = Regression Coefficient; *t* = *t*-test; Sig. = Significance

The overall regression model demonstrated statistical significance ($F(2, 79) = 4.26$, $p = 0.043$), suggesting that the predictors, when considered together, provided a meaningful explanation for the variation in student performance. The R^2 value was 0.057, indicating that the combined influence of AI integration extent and ethical practices accounts for a small but statistically reliable proportion of the variance in research class performance. While this effect size is modest, the significance of the overall model warrants interpretation of the individual predictors.

Analysis of the individual predictors confirmed the central hypothesis regarding the value of responsible use: the Adoption of the key principles in the UNESCO AI Competency Framework was a statistically significant positive predictor of research performance ($B = 1.288$, $t = 2.083$, $p = 0.041$). This strong finding suggests that students who are more mindful of ethical considerations, critical reflections, and human agency in their use of AI tend to achieve notably better academic outcomes in their research courses. This outcome reinforces that the quality of AI literacy is more important than the mere quantity of use.

Conversely, the Extent of Integration of AI Tools was not a significant predictor of performance ($B = -0.150$, $t = -0.399$, $p = 0.691$). The non-significant and slightly negative coefficient ($B = -0.150$) carries important practical significance. It implies that simply using AI tools more frequently or integrating them across more research phases does not, in itself, translate to better academic results. This suggests that without the accompanying critical engagement and ethical oversight, tool use risks becoming "naive use", failing to enhance the core research competencies required for high performance.

In sum, these findings underscore the necessity of promoting ethical and reflective AI practices in academic training rather than focusing solely on increasing technological adoption. These results have direct implications for the instructional design and AI literacy programs in higher education.

In the present study, Table 13, the mapping of students' extent of AI use in academic research writing to the Artificial Intelligence Utilization Scale (AIUS) framework reveals a nuanced but structured pattern of adoption. The data indicate that student-researchers primarily operated within AIUS Levels 3 (AI-Editing assistance) and 4 (AI-Task completion), with all indicators reflecting AI use between 21–60%. Specifically, eight of the 13 research writing tasks were aligned with Level 3, while the remaining five corresponded to Level 4, suggesting responsible and bounded engagement with AI tools.

Table 13. Mapping students' extent of AI use in academic research writing to the Artificial Intelligence Utilization Scale (AIUS) framework

AIUS level reached	Indicators aligned	Proportion of tasks
Level 1: No AI Level of AI Used: 0%	Absence of Level 1	-
Level 2: AI-idea Generation Level of AI Used: 0%	Absence of Level 2	-
Level 3: AI-Editing Assistance (21–40% AI involvement)	Research-topic generation, data collection/analysis, content structuring/formatting, statistical analysis, drafting, abstract writing, proofreading, visualization	8 of 13 tasks (62 %)
Level 4: AI-Task Completion (41–60% AI involvement)	Literature search/discovery, writing assistance & grammar, citation management, paraphrasing/summarization, plagiarism detection	5 of 13 tasks (38 %)
Level 5: Full AI Collaboration Level of AI Used: 1–45%	Absence of Level 5	-

Level 3 usage reflects activities in which AI tools support the editing process, such as grammar checking, abstract editing, proofreading, and formatting. This aligns with the AIUS principle that AI-generated outputs are refined versions of the original student work rather than AI-originated content. Level 4 tasks, such as literature review, citation and reference management, plagiarism detection, and content enhancement, indicate instances where AI was used to complete specific sub-tasks, which were subsequently evaluated and modified by the researcher. This pattern adheres to the AIUS's expectation that AI task outputs must undergo critical human assessment.

Importantly, none of the indicators fell under Level 2 (AI-Idea Generation) or reached Level 5 (Full AI Collaboration). While AI tools may have contributed to ideation and organization, they were not marked as zero-content contributions, as required in Level 2, suggesting that students may have integrated AI-generated suggestions into their writing processes. However, the absence of Level 5 usage implies a cautious approach, wherein students have yet to engage AI as co-authors or partners in deep research synthesis and narrative construction. This may be attributed to current institutional norms, ethical uncertainties, or deliberate decisions to preserve academic integrity and human agencies.

Overall, students' practices reflected a moderate but ethical adoption of AI tools, with careful differentiation between human-led and AI-supported tasks. The findings suggest that the AIUS framework effectively guided student researchers in maintaining the responsible use of AI, particularly through an emphasis on critical evaluation, transparency, and academic honesty. The dominant presence of AIUS Levels 3 and 4 demonstrates learners' inclination to use AI as a functional assistant rather than a substitute for intellectual labor, maintaining alignment with both the technical and ethical dimensions of the AIUS framework. These results provide an empirical foundation for the integration of AI competency frameworks into research instruction, highlighting the importance of structured guidance in fostering both digital fluency and reflective scholarship.

G. Discussion

These findings indicate a notable reliance among student researchers on AI tools for language-oriented and integrity-oriented tasks in academic research writing. Specifically, Scispace, ChatGPT/OpenAI, and Grammarly are the most frequently used tools. This suggests that students highly value AI to improve the clarity, coherence, and grammatical accuracy of their work, as well as to simplify technical content and extract key insights from scholarly articles. However, the use of AI has significantly declined in the more complex technical aspects of the research process, such as data collection and analysis, statistical analysis, and content structuring and formatting. This pattern suggests that students primarily use AI for "surface-level" support rather than for tasks demanding deeper methodological and critical thinking.

Furthermore, student researchers demonstrated a strong self-reported commitment to critical and ethical engagement with AI, aligning with UNESCO's AI competency framework. They agree on the importance of maintaining human agency, critical thinking, and ethical responsibility when integrating AI tools. The study also found no significant difference in the extent of AI use based on gender or academic program, indicating a generally equitable pattern of AI utilization across these demographics. Crucially, the adoption of ethical and reflective AI practices significantly predicted better research performance, whereas the extent of AI tool integration did not. This finding highlights that responsible and thoughtful AI usage, rather than frequent use, contributes to improved academic outcomes. The application of the AI Utilization Scale (AIUS) revealed that students primarily operate within Levels 3 (AI-Editing assistance) and 4 (AI-Task completion), indicating responsible and bounded engagement with AI tools and largely avoiding full AI collaboration.

The finding that AI tools are most frequently used for writing assistance, grammar checking, paraphrasing, and summarization aligns with the findings of previous studies. For example, the University of North Texas [10] and Yomu AI [13] noted that generative AI tools significantly impact academic writing by offering functionalities such as grammar, plagiarism checking, and content generation. Similarly, Uddin [57] found that ChatGPT, Grammarly, and QuillBot are widely used by undergraduate and graduate students to draft literature reviews, structure arguments, and proofread. The moderate use of AI for plagiarism detection also resonates with the growing concern for academic integrity in the age of AI.

The declining use of AI in more complex analytical tasks, such as data collection, analysis, and visualization, is consistent with the general understanding that while AI can handle large datasets and uncover patterns, human expertise remains crucial for deeper methodological and critical thinking. This suggests a gap in how students leverage AI for higher-order tasks, as highlighted by Vázquez-Parra *et al*. [25] and Roe and Perkins [26] regarding the impact on "complex thinking competence and learner's agency".

The high mean scores across the UNESCO AI Competency Framework dimensions demonstrate that students consistently adhere to ethical and human-centered principles when using AI in their research tasks. In particular, the domains related to human-centered interaction and inclusivity in AI competency development received the highest ratings, indicating that student-researchers remain mindful of authorship accountability and equitable practices when engaging with AI tools. These empirical findings substantiate the interpretation that students approach AI use responsibly within the academic context, reflecting an emerging awareness of ethical considerations aligned with institutional and global expectations for responsible AI literacy.

This strong self-reported commitment supports the growing emphasis on AI literacy and ethical AI engagement advocated by the U.S. Department of Education [4] and UNESCO [41]. Moreover, the study's regression analysis showed that ethical AI practices significantly predict research performance, while the mere extent of tool integration does not. This pattern suggests that it is not the volume of AI use that matters, but rather the quality and intentionality of engagement, consistent with the argument of Walter [44] that thoughtful AI adoption enhances academic outputs. The finding that ethical practices manifest consistently across gender and academic programs contrasts with prior results from Uddin [57], who reported gender-based caution in AI adoption, and Joseph [54], who highlighted disciplinary variations. One possible explanation for this divergence lies in the specific instructional context of the present study, where AI was actively integrated into coursework and guided by recently approved university policies promoting ethical and pedagogical AI use.

While the UNESCO AI Competency Framework establishes important ethical and human-centered guidelines for AI use, the findings of this study further align with key assumptions in educational psychology and technology-integration theories. The significant predictive effect of ethical AI practices on student performance reflects principles from the Technology Acceptance Model (TAM), which posits that perceived usefulness strongly influences behavioral intentions and learning outcomes [63]. Likewise, the Unified Theory of Acceptance and Use of Technology (UTAUT) emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of successful technology adoption [64]. These models help explain why intentional and responsible AI use, rather than simple frequency of tool exposure, contributes more meaningfully to positive academic performance. Integrating these theoretical lenses provides a deeper interpretation of the predictive results, situating responsible AI behavior within established cognitive and behavioral mechanisms of technology acceptance.

V. Conclusion

This study examined graduate students' integration of Artificial Intelligence (AI) tools in academic research using the UNESCO AI Competency Framework and the Artificial Intelligence Utilization Scale (AIUS). Findings showed that students predominantly used AI at AIUS Levels 3 and 4 focusing on editing, summarizing, and task completion rather than for higher-order analytical stages of research. While the extent of AI tool usage did not significantly predict research performance, competencies aligned with ethical, critical, and responsible AI use demonstrated a positive influence on research outcomes. These results underscore that how students use AI particularly their reflective and ethical engagement matters more than the frequency of tool usage.

The study contributes an integrated evaluative model that highlights the importance of structured pedagogical guidance. Providing access to AI tools alone is insufficient; institutions must design learning experiences that cultivate critical thinking, ethical awareness, and human-centered AI practices. Such approaches can help shift students away from surface-level usage and toward more meaningful, research-oriented engagement with AI technologies.

Several limitations should be acknowledged. The purposive sample of 81 graduate students from two academic programs limits generalizability to broader populations and disciplines. The study relied on self-reported data, which may be subject to response bias despite validated instruments. The qualitative phase used document analysis rather than direct student narratives, restricting deeper exploration of lived experiences. Finally, given the rapid evolution of AI tools and policies, findings represent a specific moment in time and may shift as technologies advance.

Future research should expand to diverse academic contexts and larger sample groups to validate and extend these findings. Incorporating interviews or focus groups is recommended to capture students' motivations, challenges, and evolving perceptions. Longitudinal studies may help trace how ethical and critical AI competencies develop over time and influence sustained research performance. Comparative analyses across disciplines and institutions would also provide a broader understanding of AI integration patterns and inform policy development.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Joseline M. Santos conceptualized the study, developed the methodology, conducted the investigation, and wrote the original manuscript. Mark Rey C. Santos performed statistical analysis and data validation. Keno C. Piad and Sergii Sharov conducted the technical review and editing of the paper, while Walton Wider was responsible for the overall review and editing. Teody C. San Andres provided supervision and the necessary resources for the study. All authors have read and agreed to the final version of the manuscript.

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