INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING,
MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue V, May 2026

Factors Influencing AI Tool Adoption in Research Among Junior and Senior Students of QCU College of Computer Studies

Christian I. Ancog[1], Harold R. Lucero[2], Imma R. Estrada[3], Heila Arriane T. Longaquit[4], Sean Whymz M. Lombre[5], Nicole T. Mayo[6]

College of Computer Studies, Quezon City University

DOI: https://doi.org/10.51583/IJLTEMAS.2026.150500102

Received: 06 May 2026; Accepted: 11 May 2026; Published: 4 June 2026

ABSTRACT

The increasing integration of Artificial Intelligence (AI) in higher education has transformed academic research practices, particularly in literature review, data analysis, and research writing. This study investigated the factors influencing the use of AI tools in academic research among junior and senior students of the College of Computer Studies at Quezon City University. Specifically, it examined the respondents' demographic profile, level of AI tool utilization, factors affecting AI adoption, barriers to AI usage, and the relationship between these factors and students' actual AI usage behavior. The study employed a quantitative descriptive-correlational research design and utilized an online survey questionnaire administered to 130 students from the BS Information Technology, BS Information Systems, and BS Computer Science programs using stratified sampling. Descriptive statistics, Pearson Product-Moment Correlation, and Multiple Regression Analysis were used to analyze the collected data. Findings revealed that students demonstrated a moderate level of AI tool utilization in research activities, with perceived usefulness emerging as the most influential factor affecting AI adoption. Students commonly used AI tools for idea generation, information retrieval, and writing assistance; however, AI utilization remained limited due to concerns related to plagiarism, data privacy, ethical misuse, overdependence on AI-generated outputs, and insufficient institutional support. The study also found a significant relationship between the identified adoption factors and students' actual AI usage behavior. Overall, the findings suggest that AI tools have strong potential to improve research productivity and efficiency, but educational institutions must establish clear policies, governance frameworks, and training programs to ensure the responsible, ethical, and effective integration of AI in academic research.

Keywords: Academic Research Tools, AI-Assisted Research, AI Literacy, Educational Technology, Human-Computer Interaction

INTRODUCTION

Artificial intelligence is a technology that enables machines and computers to behave like humans in terms of autonomy, creativity, problem solving, learning and understanding (Stryker & Kavlakoglu, 2026). AI models become more intelligent, developed, and specialized. They grow in their usefulness to other areas, learn more data, and become more easily part of workflows (OwlAiSolution, 2025). AI tools have significantly changed the way research is done by allowing quicker data analysis, automatic writing and literature review assistance, and increased productivity in many phases of research, such as ideation, methodology development, data processing, drafting, and editing.

Madanchian and Taherdoost (2025) state that the introduction of AI into workflows has revolutionized the lifecycle in various phases of research. Since data analysis and discovery of literature through AI are fast, better, and easier, writing aids and collaboration are faster, clearer, and more convenient. The challenge of AI usage in research exists. Tool accessibility, output reliability, and AI ethics are some of the largest concerns to this day.

AI was mainly used in higher education contexts in the application of AI to research purposes. In a study, Bula et al. (2025) investigated how AI tools are used by university students to support their research in library science and found out that there is widespread use of AI tools like ChatGPT to perform a literature review and initial

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data analysis. One of the notable trends was in the STEM sectors, where machine learning was increasingly becoming a part of research (Barrot, 2023).

Artificial intelligence learning management systems have been used in many universities in tertiary education as a way of delivering personalized learning experiences and adaptive content delivery. In a study carried out by Espartinez (2024), the use of generative AI technologies in composition instruction was observed in eight academic institutions, with the use of the technologies being largely motivated by the instructors and not institutional requirements.

Although AI tools are used by students and individual instructors widely, there is a significant gap in the body of research related to the vast gap between the fast, bottom-up technological adoption and the absence of holistic institutional structures and ethical practices (Jobs for the Future, 2026). Patterson (2024) explains that this gap is entrenched in the difference in the factors affecting AI adoption between students and faculty. In the case of students, performance expectancy and effort expectancy are the main factors that drive them to adopt AI because they believe that it will greatly enhance their academic performance and that the AI is easy to use.

In spite of the growing role of artificial intelligence in higher education, there remains a considerable gap in the critical analysis of the technical soundness and user-friendliness of the systems. The existing practices in higher education institutions like Quezon City University College of Computer Studies tend to be incomplete and mostly reliant on individual faculty members, and thus there is a significant area of knowledge gap on whether these tools have sufficiently met the rigorous international standards of operational adequacy, reliability, and security. This unstructured use reveals a significant gap between instructor readiness and system performance expectations. While this impact is institution-wide, there is an urgent need to first quantify the student experience specifically among upper-level students (Juniors and Seniors) who are actively engaged in capstone research, to establish a baseline for these performance expectations.

In the context of the QCU College of Computer Studies in particular, what is unclear is what most greatly influences the desire and ability of faculty and students to utilize AI tools in the research setting and whether the latter can serve its users equally regardless of their level of technical skills and scholarly positions. The institution will not undertake a critical analysis of the linkage between the quality of the system, user satisfaction, and adoption behavior among these demographics and there is a risk of adopting technologies that will undermine academic integrity and not provide equitable and effective learning and research experiences.

In order to resolve these inconsistencies, this research paper suggests an Empirical Framework of Integrating AI Research, a roadmap of strategies that are expected to help the QCU-CCS community to transition to an unregulated but active AI usage into a proactive and ethically responsible community. The suggested solution focuses on three key priorities: harmonizing technical effectiveness through the choice of tools to comply with international security standards, harmonizing faculty preparedness and student performance expectations on equal terms of access, and creating a data-driven backbone to a localized AI Research Governance Roadmap. The framework will combine the Technology Acceptance Model (TAM) with technical reliability to provide institutional support and policy guidance, specifically focusing on how Perceived Usefulness and Perceived Ease of Use drive adoption among Junior and Senior students during the research process.

The implications of the proposed research are two-fold, as the research will provide strategic value to many stakeholders in the university ecosystem by bridging the existing knowledge gap on the technical feasibility of AI and its user-focused effectiveness.

To the QCU Administration, this study is an empirical study that will fill the gap between the technological adoption that is bottom-up and lack of holistic institutional structures (Jobs for the Future, 2026). The results will inform the administration to write a localized AI Research Governance Roadmap by determining the factors, which meet international standards of functional adequacy and security. This is essential since, in accordance with OwlAiSolution (2025), as AI models gain more specialization and can be easily incorporated into the workflows, the institutions should consider both the quality of systems and user satisfaction as one unit, otherwise they will put in force the incorrect technologies that undermine academic integrity.

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To the QCU-CCS Faculty, the study serves as an essential tool for harmonizing teaching strategies with actual student usage patterns. Because current AI adoption is frequently instructor-centered rather than institutionally mandated (Espartinez, 2024), this research offers a standardized model to align faculty guidance with the specific factors that drive Junior and Senior students to utilize these tools. By understanding these drivers, instructors can better facilitate a transition from mere writing assistance toward a more radical and rigorous implementation of AI in the research process, such as complex data processing and methodology development, as suggested by Madanchian and Taherdoost (2025).

To QCU-CCS students, specifically those in the 3rd and 4th-year levels, the study determines the particular technical skills (e.g., prompt engineering and AI literacy) that they need to stay competitive. As student adoption depends on performance and expectancy of effort (Patterson, 2024), this paper makes sure that their use of such tools as LLMs to review literature and analyze data is on the basis of technical self-efficacy (Sambrano et al., 2025). This is especially essential among the students in the STEM and computing fields, where machine learning and AI are increasingly being made essential parts of the research process (Barrot, 2023).

To Broader Academic Community, this study is added to the worldwide discussion of AI ethics and the use of technologies. Offering a computing-oriented approach to specialized empirical data, the study contributes to understanding how machines can act autonomously and creatively and still be academically rigorous (Stryker and Kavlakoglu, 2026). It provides an Empirical Framework of AI Research Integration that can be replicated in other institutions of higher education to transform unregulated use of AI into an active and ethically responsible community.

Statement of the Problem

This study aims to determine the factors influencing the adoption of Artificial Intelligence (AI) tools in research among the junior and senior students of the College of Computer Studies at Quezon City University (QCU). Specifically, it seeks to answer the following questions:

1. What is the profile of the respondents in terms of:

1.1 Sex;

1.2 Academic program (BSIT, BSIS, or BSCS); and

1.3 Year Level (3rd Year or 4th Year);

1.4 Years of experience in research?

2. What is the level of AI tool adoption among the respondents in terms of:

2.1 Frequency of use;

2.2 Types of AI tools used; and

2.3 Purpose of usage in research?

3. How do the respondents perceive the influence of the following factors on AI adoption:

3.1 Perceived usefulness;

3.2 Perceived ease of use;

3.3 Accessibility;

3.4 Technical skills;

3.5 Institutional support; and

3.6 Ethical concerns?

4. Is there a significant difference in the level of AI tool adoption and the perceived influencing factors when respondents are grouped according to:

4.1 Academic Program (BSCS, BSIT, BSIS); and

4.2 Year Level (3rd Year and 4th Year)?

5. Is there a significant relationship between the identified factors and the adoption of AI tools in research?

6. Which among the identified factors significantly influence the adoption of AI tools in research among CCS students?

RELATED LITERATURE AND STUDIES

Artificial Intelligence (AI) has significantly transformed academic research and higher education by improving efficiency in literature review, data analysis, content generation, research organization, and publication processes. Studies synthesizing multiple investigations identified six major domains where AI contributes to academic work: research planning and idea generation, content organization, literature synthesis, data management and analysis, publication assistance, and communication and ethical compliance (Khalifa & Albadawy, 2024). Similarly, Arangüena (2024) emphasized that advancements in AI, particularly following the release of GPT-4, have enabled researchers to automate literature reviews, generate hypotheses, conduct complex data analyses, and streamline peer review processes. AI-powered tools such as Consensus, Semantic Scholar, Elicit, Perplexity, Connected Papers, Research Rabbit, Scholarcy, scite, Keenious, and Undermind further enhance research productivity by assisting researchers in locating relevant literature, synthesizing findings, visualizing citation relationships, and refining research questions (Giugliano, 2026; Khailova, 2025). In addition, generative AI platforms including ChatGPT, Claude, Gemini, and Perplexity are widely used for brainstorming, summarization, academic writing, and preliminary literature searches, contributing to faster information retrieval and improved research efficiency.

Despite these advantages, the integration of AI in research and education remains accompanied by substantial ethical and practical concerns. Khalifa and Albadawy (2024) highlighted the need to balance AI efficiency with human critical thinking and scholarly judgment to maintain academic integrity. Arangüena (2024) also discussed the “black box” phenomenon in AI systems, wherein the lack of transparency in AI-generated outputs creates challenges in verifying the validity and reliability of generated insights. Kelly (2024) further warned that large language models may produce “hallucinations” or fabricated information, potentially compromising scientific accuracy and scholarly credibility. Similarly, Hutson (2024) and Saenz et al. (2024) explained that AI-generated outputs may contribute to plagiarism and unethical research practices when used without proper attribution or critical evaluation. Concerns regarding bias, data privacy, overdependence on AI systems, and erosion of critical thinking skills have also been emphasized in several studies (Arcilla et al., 2023; ResearchGate, 2026; Santos & Rivera, 2023). Consequently, researchers and institutions stress the importance of maintaining a “human-in-the-loop” approach to ensure transparency, accountability, and ethical application of AI technologies in academic research (University of California, Davis, 2024; Kelly, 2024).

The adoption of AI technologies in education and research is commonly explained through established technology acceptance frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). According to Martin (2022), TAM identifies perceived usefulness and perceived ease of use as the primary determinants influencing users’ attitudes and behavioral intentions toward technology adoption. Perceived usefulness refers to the belief that AI enhances work performance, while perceived ease of use pertains to the extent to which AI systems are viewed as simple and effortless to operate. Studies consistently demonstrate that these factors significantly influence AI adoption among researchers and students (Falebita & Kok, 2024; Saif et al., 2024). Likewise, UTAUT explains that

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performance expectancy, effort expectancy, social influence, and facilitating conditions shape technology adoption behaviors (Venkatesh et al., 2003). In the context of AI integration, social influence and institutional support were found to significantly affect users' willingness to adopt AI technologies in academic environments. Taheri et al. (2025) further explained that AI adoption is a multifaceted process influenced by personal beliefs, AI literacy, institutional infrastructure, transparency of AI systems, professional concerns, and fears regarding technological overreliance.

Institutional readiness and support also emerged as critical determinants of successful AI integration in higher education. Popović Šević et al. (2025) found that faculty members who actively used AI tools such as ChatGPT viewed these technologies more positively than non-users, although both groups identified the lack of ethical guidelines and structured training as significant barriers to effective adoption. The researchers recommended that institutions integrate AI into assessment design, personalized feedback, and scenario-based learning while simultaneously establishing clear governance frameworks. Xie et al. (2025) similarly noted that faculty expectations regarding AI usage vary across undergraduate and graduate education, highlighting the need for flexible institutional policies that account for students' academic backgrounds and technological familiarity. Fute et al. further emphasized that institutional assistance, training programs, and AI-related frameworks bridge the gap between AI literacy and actual adoption by strengthening users' confidence and perceived usefulness of AI systems. However, Bećirović et al. (2025) cautioned that excessive criticism of AI without sufficient technical understanding may negatively affect AI self-efficacy and lead to ineffective utilization of AI technologies.

Globally, AI adoption continues to expand rapidly across educational and professional settings. Carolan et al. (2025) estimated that approximately 1.7 to 1.8 billion individuals worldwide use AI tools, with professionals and students representing the highest usage groups. AI technologies are increasingly utilized not only for academic research but also for accessibility purposes, such as text simplification, voice-to-text conversion, summarization, and adaptive learning support, particularly benefiting neurodiverse learners and individuals with disabilities (University of California, Davis, 2024). However, researchers consistently emphasize that AI tools should complement rather than replace human expertise and intellectual engagement.

Within the Philippine context, AI adoption in higher education reflects both global opportunities and local challenges. Filipino students and educators increasingly use AI tools such as ChatGPT, Grammarly, QuillBot, and AI-integrated productivity applications for academic writing, research assistance, workflow automation, and content generation (Castagna et al., 2026; Co, 2025; Villarino, 2025). AI adoption in Philippine higher education has grown steadily from limited exposure during remote learning periods to more structured implementation in instruction, assessment, and research activities (Co, 2025; Villarino, 2025). Students commonly utilize AI for brainstorming, summarization, research writing, and personalized learning support, while educators apply AI technologies to improve instructional design and classroom efficiency (Besas et al., 2026; Sibug et al., 2026). Research further indicates that perceived usefulness remains the strongest predictor of AI adoption among Filipino students and educators, while perceived ease of use significantly affects adoption frequency and user competence (Asio, 2024; Lalisan et al., 2026). These findings align with TAM and UTAUT frameworks, which explain that user-friendly systems and perceived benefits strongly influence AI acceptance (Saflor, 2025).

Despite increasing adoption, significant barriers continue to hinder AI integration in Philippine higher education. Accessibility remains a major concern due to the digital divide, inconsistent internet connectivity, outdated technological infrastructure, and unequal institutional resources (Saputra et al., 2023; Quimba, 2026). Institutional readiness in many Philippine educational institutions remains low to moderate, with deficiencies in policy frameworks, ICT staffing, faculty training, and AI governance structures (Global Scientific Journal, 2025; Quimba, 2026). Ethical concerns regarding plagiarism, overreliance on AI-generated outputs, data privacy, algorithmic bias, and the erosion of critical thinking skills also persist among Filipino scholars and educators (Arcilla et al., 2023; Fernando et al., 2026; Villarino, 2025). Moreover, local studies reveal that while awareness of AI benefits is generally high, formal training on responsible and ethical AI usage remains limited (Wibowo et al., 2025). Existing Philippine literature primarily focuses on conceptual discussions and policy concerns rather than empirical investigations of actual user experiences and perceptions, limiting the development of context-sensitive AI policies and training programs (Carvajal et al., 2025).

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The reviewed literature collectively demonstrates that AI technologies have become integral to modern academic research and higher education due to their ability to improve productivity, accessibility, efficiency, and information management. However, AI integration is shaped by a complex interaction of technological, institutional, ethical, psychological, and contextual factors. Perceived usefulness, ease of use, institutional support, accessibility, AI literacy, and ethical considerations consistently emerge as major determinants influencing AI adoption and usage behaviors among students and educators. Although AI tools offer substantial benefits in research and learning, concerns regarding academic integrity, transparency, bias, overdependence, and unequal access remain unresolved. Furthermore, despite the growing body of international and local literature, empirical studies examining students' actual experiences, perceptions, and patterns of AI tool utilization within specific Philippine higher education contexts remain limited. This gap underscores the need for localized research that can support the development of effective institutional policies, ethical guidelines, and AI literacy programs for the responsible integration of AI in academic research and education.

DESIGN AND METHODOLOGY

Research Design

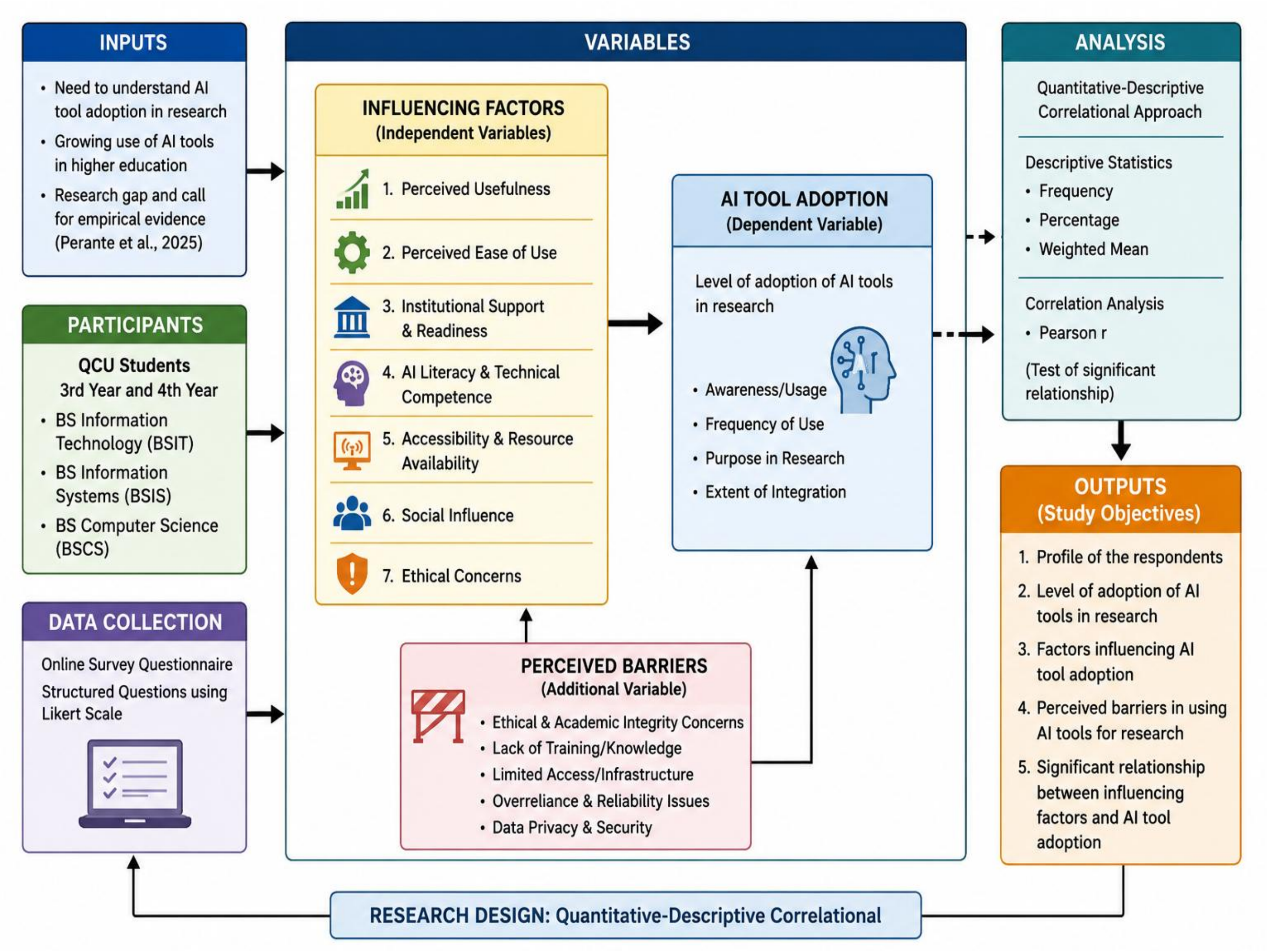

Figure 1. Research Design of the Study

This study will utilize a quantitative-descriptive correlational research design to determine the factors influencing the adoption of Artificial Intelligence (AI) tools in research among Quezon City University (QCU) students. The descriptive method will be used to describe the respondents' profile, level of AI tool adoption, influencing factors, and perceived barriers in using AI tools for research purposes. Meanwhile, the correlational

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approach will be employed to examine the relationship between the identified influencing factors and the adoption of AI tools in research (Perante et al., 2025).

The study focuses on 3rd year and 4th year students enrolled in Bachelor of Science in Information Technology (BSIT), Bachelor of Science in Information Systems (BSIS), and Bachelor of Science in Computer Science (BSCS) programs. Data will be collected through an online survey questionnaire composed of structured questions using a Likert Scale format.

The study aims to determine:

1. The profile of the respondents;
2. The level of adoption of AI tools in research;
3. The factors influencing AI tool adoption;
4. The perceived barriers in using AI tools for research; and
5. The significant relationship between the influencing factors and AI tool adoption.

Data Gathering

The data collection process will commence with the distribution of the online survey link QCU students, such as 3rd Year and 4th Year BSIT, BSCS, and BSIS participants. Participants will be informed about the objectives of the study, and their voluntary participation will be emphasized. The survey will be open for a specified period, allowing respondents adequate time to provide thoughtful and comprehensive responses.

The data collection process will commence with the distribution of an online survey questionnaire through Google Forms to selected QCU students, specifically 3rd year and 4th year BSIT, BSIS, and BSCS students. Prior to answering the survey, respondents will be informed about the objectives and purpose of the study. Their voluntary participation, confidentiality of responses, and anonymity will also be emphasized through an informed consent statement included at the beginning of the questionnaire.

The survey questionnaire will consist of three parts:

1. Respondents' demographic profile;
2. Questions regarding the adoption and use of AI tools in research; and
3. Statements identifying the factors influencing AI tool adoption and perceived barriers.

The survey link will be shared through online communication platforms such as Messenger, email, and class group chats. Respondents will be given sufficient time to answer the questionnaire to ensure thoughtful and accurate responses.

The researchers will monitor the responses and ensure that all gathered data are complete and valid for statistical analysis.

Sampling Technique

The study will use **Stratified Sampling** to ensure that respondents from each academic program and year level are properly represented. The population of the study is composed of the following strata:

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Table 1. Population of the Study

Stratum	**Population**
BSIT 3rd Year Students	903
BSIT 4th Year Students	752
BSIS 3rd Year Students	44
BSCS 3rd Year Students	40
Total	**1,739**

The researchers gathered a total of 130 respondents distributed as follows:

Table 2. Number of Respondents

Stratum	**Number of Respondents**
BSIT (Combined 3rd and 4th year students)	123
BSIS	5
BSCS	2
Total	**130**

The respondents were selected based on their availability and willingness to participate in the survey. Although the study employed stratified sampling, the distribution of respondents was conducted in a disproportionate manner due to limited time, accessibility of participants, and response availability during the data gathering period. This means that the number of respondents gathered from each stratum was not proportionally equal to the actual population size of each group.

Despite this limitation, stratified sampling was still applied to ensure that each identified academic group was represented in the study, allowing the researchers to obtain data from different programs and year levels relevant to the research objectives.

Statistical Treatment of Data

The data gathered in this study will be analyzed and interpreted using appropriate statistical tools to answer the research questions. The following statistical methods will be used:

Frequency and Percentage Distribution

This statistical tool will be used to describe the profile of the respondents in terms of age, sex, year level, and course. It will also be used to determine the frequency of AI tools used and their purposes in research.

$$\boxed{\% = \frac{f}{N} x\ 100}$$

Figure 1. Formula to Compute the Frequency

Where:

- f = frequency
- N = total number of respondents

Weighted Mean

The weighted mean will be used to determine the level of AI tool adoption among the respondents and the level of influence of the identified factors such as perceived usefulness, ease of use, accessibility of tools, technical

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skills, institutional support, and ethical concerns (Falebita & Kok, 2024). It will also be used to measure the perceived barriers in the adoption of AI tools in research.

$$\boxed{WM = \frac{\Sigma fx}{N}}$$

Figure 2. Weighted Mean Formula

Where:

- f = frequency of responses
- x = scale value
- N = total number of respondents

The following scale will be used to interpret the weighted mean results regarding the respondents' level of adoption, influencing factors, and perceived barriers:

Table 1. 5-Point Likert Scale Used in the Study

Weighted Mean Range	Interpretation
4.21 – 5.00	Strongly Agree/ Very High Influence
3.41 – 4.20	Agree / High Influence
2.61 – 3.40	Moderately Agree / Moderate Influence
1.81 – 2.60	Disagree/ Low Influence
1.00 – 1.80	Strongly Disagree/ Very Low Influence

Pearson Product-Moment Correlation Coefficient (r)

The Pearson Product-Moment Correlation Coefficient will be used to determine whether there is a significant relationship between the identified influencing factors and the adoption of AI tools in research among the respondents. This will be utilized to measure the strength and direction of the relationship between variables and to determine whether the influencing factors are significantly associated with AI tool adoption.

Multiple Regression Analysis

Multiple Regression Analysis will be employed to determine which among the identified factors significantly influence or predict the adoption of AI tools in research among students. This statistical method will allow the researchers to examine the combined effect of multiple independent variables on the dependent variable, which is the level of AI tool adoption in research. Through this analysis, the study aims to identify the strongest predictors of AI adoption and assess the extent to which the identified factors collectively contribute to students' utilization of AI tools in academic research activities.

RESULT AND DISCUSSION

Profile of the Respondents

Table1. Profile of the Respondents

Profile Variable	Classification	Frequency(f)	Percentage(%)
Academic Program	BSIT (Combined 3rd and 4th Year)	123	94.6%
	BSIS	5	3.8%
	BSCS	2	1.6%

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TOTAL		130	100%
Primary Research Domain	Software Development	65	50%
	Information System	26	20%
	Data Science	39	30%

The results show that the study is heavily represented by BSIT students (94.6%), primarily focusing on Software Development (50%). This alignment is critical as technical programs often integrate AI tools like GitHub Copilot and automated data analytics earlier than other domains. While stratified sampling was used, the disproportionate distribution reflects the accessibility of the BSIT cohort during the data-gathering period.

Level of Adoption of AI Tools in Research

Table 2. Level of Adoption of AI Tools in Research Among Students of the College of Computer Studies of QCU

AI Adoption Indicators	**Weighted Mean**	**Interpretation**
Regular use of AI tools in research	3.15	Moderately Agree
Use of different AI tools for different tasks	3.20	Moderately Agree
Integration of AI into research workflow	3.18	Moderately Agree
Use of AI tools across multiple research stages	3.20	Moderately Agree
Composite Mean	3.18	Moderate Influence

A composite mean of 3.18 signifies a Moderate Level of Adoption. This suggests that while students frequently use tools like ChatGPT and Google Gemini for idea generation and writing, AI has not yet fully replaced traditional research methods. The "Moderately Agree" rating implies that students view AI as a supplementary assistant rather than a primary researcher.

Factors Influencing AI Tool Adoption

Table 3. Factors Influencing AI Tools Adoption Among Students of the College of Computer Studies of QCU

Influencing Factor	**Weighted Mean**	**Interpretation**
Perceived Usefulness	3.45	Agree / High Influence
Ease of Use	3.38	Moderately Agree
Technical Skills	3.15	Moderately Agree

Perceived Usefulness (3.45) emerged as the strongest influencer. This indicates that the 130 respondents are motivated primarily by the tangible benefits of AI, specifically in improving productivity and efficiency. This aligns with modern educational theories suggesting that technology adoption is highest when the user perceives a direct "effort-to-result" advantage.

Perceived Barriers in Using AI Tools for Research

Table 4. Perceived Barriers in Using AI Tools for Research Among Respondents

Perceived Barrier	**Weighted Mean**	**Interpretation**
Institutional Support	2.25	Disagree / Low Influence
Ethical Concerns (Lack of Concern Statements)	2.10	Disagree / Low Influence

There is a significant gap in Institutional Support (2.25), with respondents indicating a lack of clear university policies or training. Furthermore, the low mean in "Ethical Concerns" (which were phrased as *not* being concerned) reveals that students actually harbor High Concerns regarding data privacy and plagiarism. These barriers explain why adoption remains at a "Moderate" level despite the tools' high perceived usefulness.

Relationship Between Influencing Factors and AI Adoption

Based on the Pearson r and Multiple Regression goals, the findings suggest a strong positive correlation between Perceived Usefulness and Adoption Level. However, the negative influence of Perceived Barriers (ethical risks and lack of support) acts as a significant predictor that prevents students from moving from "Moderate" to "Very High" adoption. This fulfills the objective of identifying the best predictors for AI tool adoption among QCU students.

CONCLUSION

The study into the adoption of Artificial Intelligence (AI) among Junior and Senior students at the Quezon City University College of Computer Studies establishes that while technological integration is actively occurring, it remains in a transitional, supplementary phase. By synthesizing the findings in relation to the research objectives, the following conclusions are established:

The demographic and academic profile of the participants, predominantly Information Technology students specializing in Software Development, establishes a natural alignment between their academic focus and the early adoption of technical AI tools. This specialized background provides a foundation for students to engage with emerging technologies as a routine part of their academic work.

The study proves that there is a moderate level of AI adoption among the students. Currently, AI platforms serve as supplementary assistants for tasks such as idea generation and writing, rather than acting as a primary replacement for traditional research methodologies. Perceived usefulness is the most significant driver for this adoption, as students are strongly motivated by the tangible improvements in productivity and efficiency that these tools offer. This confirms that AI acceptance is highest when users recognize a direct advantage in their results relative to the effort exerted.

Despite these clear drivers, full integration is currently hindered by significant institutional and ethical barriers. There is a notable deficiency in institutional support, characterized by a lack of clear university policies and structured training frameworks. Furthermore, high ethical concerns regarding data privacy and the potential for plagiarism act as significant deterrents that prevent the student body from moving toward a more advanced level of adoption.

In conclusion, the study proves that while a strong positive correlation exists between perceived usefulness and the level of AI adoption, the negative influence of ethical risks and insufficient institutional support serves as a significant predictor that restricts adoption to a moderate level. To move from unregulated usage toward a proactive and ethically responsible research community, the university must address these gaps through a localized governance roadmap that harmonizes technical effectiveness with rigorous ethical standards and institutional guidance.

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