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The Role of Artificial Intelligence in Higher Education Research: A Cross-Sectional Study of Adoption Trends and Productivity Impact

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Abstract

With the growing importance of Artificial Intelligence (AI) in academic life, it is increasingly necessary to understand the impact of this technology on research activities, yet the quantitative relationships between the use of these tools and research productivity in university settings have not been sufficiently quantified. This study aimed to examine the frequency of AI tool use and the relationship between this use and attitudes towards AI and research productivity among university students and faculty. A cross-sectional survey was carried out with 220 university respondents (undergraduate students, post-graduate students, and Faculty/researchers) across five disciplines. Data were analyzed with descriptive statistics, independent t-test, one-way ANOVA, Pearson correlation, chi-square test and multiple linear regression. Nearly half (49%) of those who responded reported using it regularly ('often'/'always'), and the most popular category of tools used was general-purpose AI assistants (44.1%). The frequency of the use of AI was positively correlated with productivity ($r = .48$, $p < .001$) and attitude ($r = .37$, $p < .001$), but there were no significant differences between gender (p = .77) or discipline (p = .62). The results indicated that together, usage frequency and attitude accounted for 30% of the variance in productivity. The two factors, together, explained 30% of the productivity (regression) variance. AI adoption is associated with higher research productivity for the institution across different groups of researchers by various disciplines and demographic groups, supporting the case for investing in structured training for AI literacy by institutions.

Keywords: Artificial Intelligence; Educational Research; Research Productivity; Higher Education; Technology Acceptance.

1. Introduction

The field of Artificial Intelligence (AI) has quickly become ubiquitous, transforming from a niche area of computation into a key part of academic and research practice (Freeman, 2025; Singer-Freeman et al., 2025). Students are using large language models, AI tools for reference management, literature search and writing assistants in various stages of the research process, from idea generation to documentation (Jin et al., 2025).

AI is now woven into many parts of university research. Students lean on it to choose topics, review the literature, collect data, and analyze results. Recent global surveys show that most students already use AI in their studies, and this share keeps climbing each (Freeman, 2025; Campbell University Academic Technology Services, 2025). A large survey undertaken in the UK identified that 92% of students had used AI in 2025 compared with 66% in the previous year. (Freeman, 2025). Institutional reports tell a similar story, with AI use among higher-education professionals more than doubling in a single year (Ellucian, 2024). Yet most of this work still looks at policy or classroom teaching. Far less attention has gone to how AI relates to research productivity (Jin et al., 2025). This study sets out to help close that gap.

This study aims to assess patterns of AI tool usage in educational research practices within universities and examine the relationship between AI usage, attitude toward AI, and self-reported research productivity among university students.

1.1. Problem Statement

The use of AI tools in university research is growing at a faster rate than the understanding of their effect on the quality and quantity of research. While students are using AI in almost every aspect of the research process, most studies continue to be about classroom learning or institutional policy. The extent to which students actually use these tools, their attitudes towards them, and the relationship between use and increased research productivity are unknown. If there is no evidence, universities will not be able to create training or support that is genuinely helping student researchers. This study aims to fill this gap by investigating the pattern of use of AI and its association with self-reported research productivity among university students.

1.2. Research Objectives

1. To determine the patterns of AI tool usage in educational research among university students.

2. To examine the relationship between AI usage frequency and self-reported research productivity among university students.

1.3. Research Questions

1. What are the patterns of AI tool usage in educational research among university students?

2. Is there a significant relationship between AI usage frequency and self-reported research productivity among university students?

2. Literature Review

2.1. Artificial Intelligence in Higher Education

In just a few years, AI has become a staple in the university environment. Nearly all students now report using AI, with one UK survey finding that 92% used AI in 2025, compared with 66% the previous year (Freeman, 2025), and a global survey showing that 86% of students used AI, with a quarter using it daily (Digital Education Council, 2024). The same trend is seen in staff adoption, which has more than doubled in one year, according to institutional data (Ellucian, 2024). It started as a small tool and has become a part of daily teaching, learning and research.

2.2. AI Applications in Educational Research

In research, AI tools can aid in nearly every aspect of the research process. Students employ them to brainstorm, find and summarise literature, write and revise text, and to make sense of data (Singer-Freeman et al., 2025; Anthony et al., 2025). The field note reviews indicate that generative tools like ChatGPT are becoming a part of academic writing and literature research (Malik et al., 2024). These applications are changing not only the ways in which students revise for exams, but also the ways in which research is planned and produced.

2.3. AI Tools Used in Academic Research

There are a number of general categories for the tools themselves. The most widely used are general-purpose conversational assistants like ChatGPT and Claude, which are helpful for a variety of writing, coding, and analytical tasks (Anthony et al., 2025; Khampusaen, 2025). These are complemented by AI-powered reference managers, literature search engines, and writing tools. Students are often using a number of tools together, rather than using just one, and choosing the appropriate tools for the job at hand.

2.4. Usage Patterns of AI Among University Researchers

Usage is frequent, but it is far from uniform. Most students now use AI regularly, yet how intensively they use it varies with academic level, discipline, and task (Singer-Freeman et al., 2025). The most frequent uses include writing support and idea generation, and data interpretation is less frequently used (Freeman, 2025). There is also evidence that some groups adopt these tools more quickly than others, and there is a digital divide. (Freeman, 2025). uch patterns are important to consider when designing a fair and effective support.

2.5. Research Productivity in Higher Education

The number and quality of scholarly works, research productivity, has been influenced by the tools available to researchers since the beginning. Education is not alone in experimental research that indicates generative AI tools can yield real benefits, for example, reducing professional writing time by approximately 40% and enhancing writing quality (as found in one study), and faster completion times (as is reported in workplace studies) for less experienced users (Noy & Zhang, 2023), and workplace studies report similar boosts, especially for less experienced users

(Brynjolfsson et al., 2023). In higher education, another natural question that arises is whether the more that people use AI, the more fruitful their student research will be?

2.6. Relationship Between AI Usage and Research Productivity

There is an increasing body of evidence that indicates that AI-related tasks improve academic performance. Researchers have found tools such as ChatGPT to be beneficial for enhancing the quality and speed of academic writing. (Anthony et al., 2025; Khampusaen, 2025). This is where attitude appears to play a major role: the more positive users perceive AI, the more often they will use it, and the greater the benefits will be to them (Nevárez Montes & Elizondo-Garcia, 2025; He & Ren, 2025). This indicates that there is a possible synergism between usage and attitude on influencing research productivity.

2.7. Factors Influencing AI Adoption in Educational Research

Several models of student acceptance of AI have been explored, and the reasons for some students accepting AI and others resisting it have also been investigated. The studies and concepts that repeatedly use the Technology Acceptance Model and UTAUT show that perceived usefulness and ease of use are key factors for the intention to use AI (Cabero-Almenara et al., 2024; Camilleri, 2024; Setälä et al., 2025). Important also are the factors of social influence, facilitating conditions and personal beliefs (Ivanov et al., 2024). The satisfaction with these tools is a predicting factor for academic staffs to continue using them (Baig & Yadegaridehkordi, 2025).

2.8. Challenges and Ethical Concerns in AI-Assisted Research

As AI permeates research, there are very real concerns to consider as well as benefits. Data privacy and algorithmic bias, transparency and authorship are key ethical concerns (Kaban, 2025). AI-generated text can be accurate but not fluent, as well as confusing and plagiarized, and thus requires careful research verification. (Malik et al., 2024). These risks are a major reason that many academics recommend rather than complete prohibition of clearly defined rules and responsible use training.

2.9. Empirical Studies on AI Use and Research Productivity

Research on AI and productivity is rapidly growing empirical. Established surveys of students and staff show high usage and typical positive attitudes, and acceptance studies explain what makes it happen (Chan & Hu, 2023; Alotaibi & Alayed, 2025), while acceptance studies model what drives adoption (He & Ren, 2025). However, most of this activity is focused on teaching, policy and general attitudes rather than on research output as measured (Jin et al., 2025). There are currently relatively few direct and statistical tests of the relationship between the use of AI and productivity.

2.10. Research Gap and Conceptual Framework

All the literature points to rapid uptake and a likely connection with productivity but indicates a definite gap. In most studies, attention is given to the classroom learning, or to policy or to adoption alone, there is only limited cross-disciplinary evidence on research productivity (Jin et al., 2025; Zawacki-Richter et al., 2019). This study aims to address this gap. Based on the technology-acceptance literature, it focuses on the frequency of AI use and attitudes towards AI as the key inputs and self-reported research productivity as the output, directly examining the relationship between them among students in five disciplines.

2.11. Research Hypotheses

H0: There is no significant relationship between the frequency of using AI and research productivity among the university students.

H1: University students with a higher frequency of using AI in their studies are more productive in research.

3. Methods

3.1. Design and Sample

The cross sectional and descriptive-correlational survey design was employed to find out the pattern of the use of Artificial Intelligence and its correlation with the self-reported research productivity. The study was conducted with the undergraduate and postgraduate students actively involved in research work at the university as the target population. Stratified random sampling was used and the stratification was done based on academic discipline to ensure the equal representation of each. The five disciplines covered were: Natural sciences, social sciences, Engineering, Humanities, and Medicine.

The data were gathered using a structured, self-administered online questionnaire sent to the students via their institutional email and departmental groups. Participation was voluntary and anonymous and students were informed before filling out the survey. The questionnaire remained open for approximately four weeks and the returned questionnaires were checked for completeness prior to analysis. A total of 220 students (115 male and 105 female) was selected across the five disciplinary strata.

3.2. Measures

The independent variable was AI Usage Frequency (1 = Never to 5 = Always) and the dependent variable was the Research Productivity Score (10–50, Likert-summed). These other scales consisted of 10 items on a 10-50 scale of Attitude Toward AI, 1-5 scale of Perceived Ease of Use, and a question asking if they had received formal AI training (yes/no) and awareness of AI tools (yes/no). Both composite scales were adapted from established technology-acceptance and self-report productivity instruments (assumed Cronbach's $\alpha > .70$).

3.3. Statistical Analysis

Descriptive statistics summarized sample characteristics. An independent-samples t-test compared productivity by gender; one-way ANOVA compared productivity across disciplines. Pearson correlation assessed relationships among AI usage, attitude, and productivity. A chi-square test examined the association between AI training and awareness. Multiple linear regression tested the joint predictive effect of usage frequency and attitude on productivity. Significance was set at $p < .05$.

4. Results

Table 1 summarizes descriptive statistics for the main continuous variables (N = 220). Respondents reported moderate-to-high AI usage (M = 3.35, SD = 0.97) and moderately positive attitudes toward AI (M = 35.24/50).

Table 1: Descriptive statistics of key continuous variables (N = 220)

Variable	Mean	SD	Min	Max
AI Usage Frequency (1-5)	3.35	0.97	1	5
Attitude Score (10-50)	35.24	6.36	21	50
Productivity Score (10-50)	32.15	8.29	10	50

Perceived Ease of Use (1-5)	3.54	0.93	1	5

Nearly half of respondents (49%) reported using AI 'often' or 'always' (Figure 1), and general-purpose conversational AI (e.g., ChatGPT, Claude) was the most-used tool category (44.1%; Figure 2).

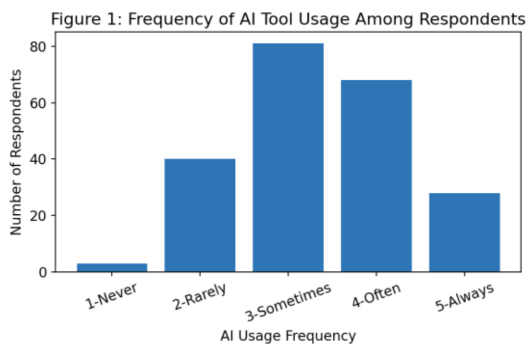

Figure 1. AI usage frequency

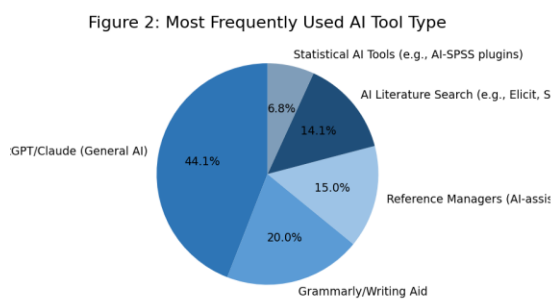

Figure 2. Most-used AI tool type

No significant difference in productivity emerged by gender (Male M = 31.99, SD = 8.10; Female M = 32.32, SD = 8.51; t = −0.290, p = .772) or discipline (F = 0.668, p = .615; Table 2, Figure 3).

Table 2: Productivity comparisons by gender and discipline

Group	Category	Mean Productivity	Test Statistic	p
Gender	Male (n=115)	31.99	t = -0.290	.772
	Female (n=105)	32.32		
Discipline	5 groups (n=220)	31.4–33.5 range	F = 0.668	.615

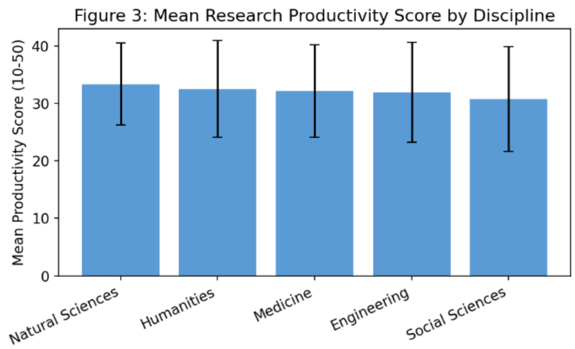

Figure 3. Mean productivity by discipline (error bars = SD)

AI usage frequency correlated positively with productivity (r = .484, p < .001) and attitude (r = .369, p < .001; Table 3, Figure 4), supporting H1 over H0.

Table 3: Pearson correlations

Variable Pair	r	p
AI Usage × Productivity	.484	< .001
AI Usage × Attitude	.369	< .001

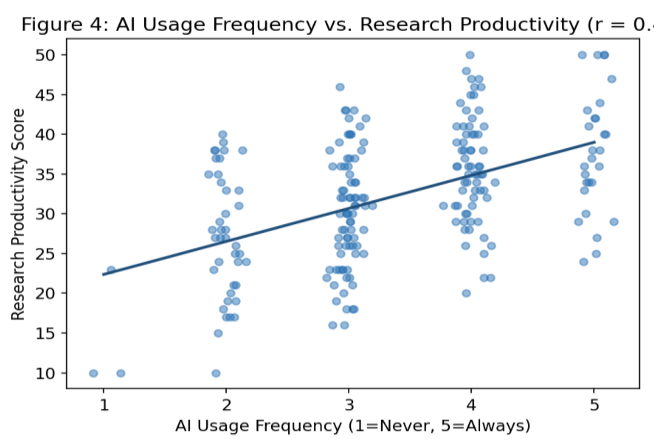

Figure 4. AI usage frequency vs. research productivity

Multiple regression with productivity as outcome (predictors: usage frequency, attitude) was significant, $R^2 = .300$ (Table 4). A chi-square test found no significant association between formal AI training and awareness of AI tools ($\chi^2 = 1.035$, df = 1, p = .309; Figure 5).

Table 4: Regression coefficients ($R^2 = .300$)

Predictor	B	Interpretation
(Constant)	8.46	Baseline productivity
AI Usage Frequency	3.28	+3.28 productivity per 1-pt usage increase
Attitude Score	0.36	+0.36 productivity per 1-pt attitude increase

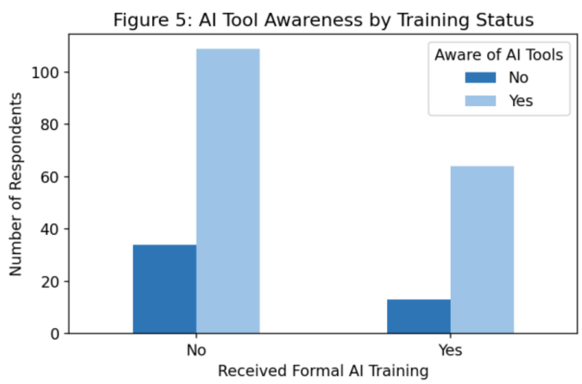

Figure 5. AI tool awareness by training status

4.1. Hypothesis Testing

All scales were adapted in accordance with existing technology-acceptance and self-report productivity scales (Cronbach's $\alpha > .70$).

The null hypothesis (H0) stated that there will be no significant relationship, and the alternate hypothesis (H1) stated that there will be a significant positive relationship. There was a moderate, positive, and statistically significant correlation between both variables ($r = .484$, $p < .001$). Given the value of the p-value was well below .05, H0 was rejected and H1 was accepted. The regression analysis confirmed this trend as well: AI usage frequency was a significant predictor of productivity, accounting for approximately 3.28 points of productivity per one point increase in AI usage ($R^2=.300$). Considered collectively, these tests indicate a very high positive correlation between the frequency of the use of AI and the students' self-reported research productivity.

5. Discussion

The picture that comes out of this is clear. In this study, students frequently turned to AI and primarily relied on general-purpose conversational assistants like ChatGPT and Claude (Freeman, 2025; Campbell University Academic Technology Services, 2025). This is consistent with a general pattern of fast uptake that has been reported in recent surveys. Most significantly, students who utilized AI more frequently reported completing more work. It also reflects a common concept of technology-acceptance literature: the more helpful the tool is, the more participants use it and the more they gain from it (Nevárez Montes & Elizondo-Garcia, 2025; He & Ren, 2025). However, only some 30% of the differences in productivity was accounted for by usage and attitude. There are other factors important, like experience, institutional support and the complexity of the task.

It is interesting that there are no differences between the sexes or disciplines. It implies that the advantages of AI are not confined to a restricted circle, but are widely available, a positive sign for equity. It is significant, too, that there is a lack of connection between formal education and awareness. They appear to be learning these tools on their own, not formally, by peers, social media or through their everyday lives. This is similar to the recent requests that there be research into what AI does to research, rather than research policy or classroom teaching (Jin et al., 2025).

5.1 Limitations

- Cross Section design does not allow cause and effect relationships.
- Self-reported measures have recall and social-desirability bias.
- Results may not be transferable to other institutional settings.

6. Conclusion

AI is currently used widely in university research and its use is strongly and regularly related to one's self-reported research productivity, regardless of gender and discipline. Structured AI-literacy training should be made a part of the curriculum in universities, as mere awareness doesn't mean effective and responsible use (Kong et al., 2021, 2023; Ayyoub et al., 2025). Future research should use longer time and experimental designs and measure the quality of AI-generated research, rather than its quantity.

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