

The Role of Artificial Intelligence in the Development of Research Competencies and Academic Inquiry Skills in Higher Education

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ABSTRACT:

AI is increasingly a part of higher education, with its impact on student search, evaluation, synthesis, and communication of academic information. Its contribution to the development of research competencies and academic inquiry skills among different learners, such as students with disabilities, specific learning difficulties, and academic support needs however, has not been sufficiently explored. This study explored the correlation between academic growth, skills retention, and research skills indicators in higher education and AI engagement. A secondary quantitative design was used for the dataset of this study, which is publicly available, AI Usage & Student Academic Performance Analysis, consisting of 50,000 student records. Preprocessing, construct development, descriptive analysis, comparison of groups using AI, ANCOVA, machine learning prediction and explainable feature-importance analysis were performed using a Python notebook-based workflow. Moderate use of AI was found to be correlated with increased GPA gain, skills retained, academic inquiry proxy, and research competency proxy. The frequency of using AI was not sufficient to predict the skill of prompt-engineering or tool diversity, or baseline academic performance or traditional study hours. The study is summarized as follows: AI can be most useful in guiding inquiry when it is a "guided construct and scaffold" that is ethical, accessible, and inclusive. It provides an empirical modelling framework for research learning with AI support in inclusive higher education.

Keywords: Artificial intelligence, research competencies, academic inquiry, higher education, inclusive education

1. Introduction

AI is a powerful player in higher education, changing the way students find information, process it, and write academically, as well as how they are given feedback and how they are challenged in deeper learning. Previous studies of the use of AI in higher education reported a growing trend with the use of AI in profiling, prediction, assessment, adaptive systems and

intelligent tutoring, but also highlighted the lack of pedagogical approaches and of educator's involvement [1]. More recent research has validated that AI in higher education has evolved beyond merely being a technology to a significant field of study that focuses on teaching and learning, institutional policies, academic support, and student development [2]. The implementation of AI in this context extends

beyond mere efficiency to the very nature of learning, influencing how students approach academics, conduct research, and solve problems. AI's power in education can be described in three different ways: as an AI-directed form, AI-supported, and AI-empowered learning paradigm [3]. The difference is important because research skills and competencies and skills of academic inquiry aren't just a matter of "digital access". Students should be able to ask relevant questions, assess information, make sense of information, think logically, and express their results in an academically honest manner. These requirements are especially significant for students with disabilities, students with specific learning difficulties, neurodiverse profiles, language-related barriers, and students who have

other academic-support needs, which may necessitate accessible and differentiated possibilities for entering academic inquiry. But there is a concern that generative AI might cause users to rely excessively on AI to brainstorm, explain, draft, summarize, revise and give feedback instead of thinking critically. Thus, implementing AI in Universities should be guided by policies, ethics, and pedagogic aspects, rather than indiscriminately [4]. Students' attitudes towards generative AI demonstrate both opportunities and risks. Although students appreciate the efficiency, boost in confidence, personalized support and access to academic support that AI tools provide, they also acknowledge some concerns about reliability, dependency, fairness and responsible use [5]. The above issues are particularly pertinent in the context of inclusive HE, where access to higher education may be influenced by disability, cognitive difference, AT, digital literacy and institutional support. AI can be useful as an academic scaffold to help process language, clarify ideas, plan, revise, comprehend, and access learning materials. Without careful oversight, however, AI has the potential to perpetuate inequities, potentially elevating the performance of students who are more adept at using digital technology and creating reliance for others who require structured guidance. One of the areas where the impact of AI can be seen is academic

writing and inquiry. Generative AI can support students in the drafting and revision process; however, it also has implications for authorship, originality, feedback and teacher assessment [6]. Large language models offer potential for personalization, formative assessment, and active learning, but also pose challenges in the areas of misinformation, hallucination, bias, privacy, and diminished critical thinking skills [7]. This is related to academic integrity issues as AI-generated content can make it difficult for students to distinguish between acceptable study aids and academic dishonesty when they are not explicitly instructed to use AI in a clear and responsible manner [8]. Thus, it is not only important to research the development of research competencies in AI-supported higher education about its performance, but also as an ethical, accessibility, and pedagogical problem. This study's problem is the lack of understanding of how AI can be used to develop research competencies and academic inquiry skills, especially about inclusive and special education. There is a lot of talk about the use of AI, academic integrity, or performance of the technology, but little about how AI engagement, prompt engineering skill, tool diversity and study behaviour correlates with observable indicators of inquiry and research competency. When considering the use of AI tools by diverse learners, ethical AI principles in education highlight transparency, fairness, privacy, accountability, and human agency [9]. Meanwhile, the hybrid intelligence viewpoints propose that AI ought to be utilized as an aid to, not a replacement for, human inquiry, judgment, and reflective learning [10]. This study is limited to the secondary quantitative analysis of data from a publicly available survey on AI usage and academic performance of the Higher Education students. There are no direct standardized measures of research competency, academic inquiry, disability status, or special educational needs in the dataset; instead, these concepts are explored using proxy measures such as GPA gain, skill retention, prompt-engineered skill, AI engagement, and created competency measures. The study is not a randomized causal study. Rather, it looks at relationships and differences

between groups, as well as predictive patterns and explainable model outputs that could help to explain how AI engagement is connected to academic inquiry and research competency development. The research is important because it adds to the body of knowledge about inclusive higher education and special education research. The study explores AI-supported academic development across measurable markers to provide evidence to educators, disability support, academic support units, and institutions for developing responsible use of AI for all learners. The study has three objectives, namely:

- To examine how AI engagement is associated with research competency and academic inquiry indicators among higher education students.
- To compare academic and competency-related outcomes across low, moderate, and high AI-use groups.
- To identify the strongest predictors of research competency development using statistical modeling and explainable machine learning.

2. Literature Review

The field of artificial intelligence in education has transitioned from a broad optimism about technology to a more specific focus on pedagogy, learner agency, ethics, accessibility, and evidence-based implementation. There are other studies that indicate that AI can be used to assist in adaptive learning, automated feedback, learner modeling, prediction, assessment, and personalized instruction. The field also has concerns regarding explainability, bias, data privacy, teacher readiness, educational validity, as well as concerns about using AI as a replacement for human judgment instead of a scaffolding for learning [11]. This has a direct implication for research competency development as research involves questioning, evaluating evidence, synthesis, methodological reasoning and reflective judgment, rather than the automatic retrieval of information.

In general, other studies on AI in education demonstrate that AI technologies such as

machine learning, natural language processing, learning analytics, and intelligent tutoring systems have been extensively employed for prediction, recommendation, assessment, and support of learners. These are useful to consider, as they offer a scalable academic support and have the potential to detect behaviors trends among learners. However, their shortcoming is that many of these studies focus on the technical achievement rather than the pedagogical significance, inclusive entitlement or the acquisition of higher order academic skills [12]. Thus, while AI systems can enhance efficiency and personalization, their role in research skills and academic inquiry is not well-defined.

The use of generative AI and chatbot-like systems has also brought some changes to the discussion, as they engage directly with the student during the writing, questioning, summarizing, and problem-solving process. Chatbots can serve as approachable learning assistants, providing instant explanations, feedback, and academic assistance. Meanwhile, they also pose threats in terms of incorrect data, excessive trust, superficial learning, plagiarism, and uncritical adoption of AI texts [13]. In special and inclusive education, this dual function is significant as AI could be used to assist students who require extra support, while also running the risk of heightening the reliance on AI by not teaching students how to check, question and revise AI responses.

Generative AI is a priority in institutional responses in higher education. Guiding principles and policies for academic integrity, assessment redesign, responsible use, transparency and equity and data protection are increasingly discussed and included. Institutional responsibility and individual responsibility are both included, for these are effective approaches, because they recognize that using AI is not an individual student issue, but an institutional one. But policies are sometimes general and fail to clarify exactly how the use of AI affects students' learning outcomes like skill retention, research competency, or academic inquiry development [14]. This leaves a gap between institutional AI regulation and what happens in learning with AI.

Human-centered approaches in learning analytics and AI emphasize transparency, explainability, and human-centered goals in the use of AI in learning. They are strong, emphasizing that they oppose purely automated decision making, emphasize trust, accountability and agency of learners. But many AI models used in learning are not easy to interpret and models that yield prediction results and do not explain the inputs to the models, such as variables about the learner that influences the output. In the present study this limitation is justified by using the explainable modeling that explains the importance of predictors of research competency development.

AI research with equity in mind says that the needs of the learner are diverse, intersectional, bias must be considered, and technological resources must be considered as well. This applies particularly to learners with disabilities and specific learning difficulties and those with a neuro-diverse profile, language barriers and academic-support needs. Equitable AI models shift the dial from an average performance of the AI model to fairness, accessibility and differentiated impact. A major gap in the literature is the conceptual nature of the study of inclusive AI, and the lack of quantitative data to link AI usage with competency outcomes [16].

Studies in inclusive higher education and assistive technologies have demonstrated the potential of digital technologies to enhance the accessibility, communication, organization, participation and independence of an individual with a specific learning difficulty. New technologies such as AI tools and immersive environments can potentially extend the possibilities of supporting students who may be limited in traditional education contexts. But these technologies must be carefully designed, assessed for accessibility, and given appropriate institutional support to prevent exacerbating exclusion [17]. This has a direct impact on special education since AI needs to be assessed not just for productivity, but also for its potential to facilitate involvement in academic inquiry.

To understand AI-supported academic development, one needs to be familiar with

Assistive technology and Universal Design for Learning. Universal Design for Learning focuses on multiple ways of engagement, representation, and expression and assistive technologies can minimize obstacles for individuals with disabilities. These approaches view technology as a facilitator of access and participation and not a replacement for learning. But existing literature on AT was created before the common use of generative AI, and there are remaining concerns about the impact of AI tools on research skills, inquiry habits, and competency development [18].

Higher education accessibility studies reveal that there are several types of barriers that can be experienced by students with disabilities such as structural, digital and pedagogical. To make e-learning more flexible and accessible, accessibility must be designed in learning systems. It is widely assumed that having access to technology means that the student is “included” in the digital learning process, even though guidance, accommodations, and accessible instructional design may be necessary. Inclusive higher education research also focuses on participation, belonging, accessibility and institutional responsibility but few empirical studies also investigate the role of AI-related behaviors in the academic inquiry and the research competency outcomes [20]. To fill this gap, the present study applies secondary quantitative data, group comparison, ANCOVA, machine learning prediction and explainable feature-importance analysis to explore the relationship between AI engagement, prompt-engineering skills, tool diversity and dependency, and study behavior with research competency and academic inquiry development in higher education.

3. Methodology

3.1 Research Design

The research design used in this study was a secondary quantitative one to investigate how artificial intelligence can be used in the development of research competencies and academic inquiry skills in higher education. The study utilized an existing dataset, which is why the analysis is best described as an AI-exposure-

based comparative and predictive modeling study. Students were dichotomized by their weekly generative artificial intelligence use and statistical and machine learning models were used to test whether AI use, prompt-engineering skill, and associated learning behaviors were related to academic development, skill retention, and research competency measures.

The methodological workflow was based on five consecutive steps, including data acquisition,

preprocessing and construct development, descriptive and comparative analysis, inferential modeling, and machine learning-based prediction with model explainability. This framework enabled the research to go beyond mere descriptive reporting and test statistical relationships and predictive patterns in the correlation between AI usage and academic skill improvement.

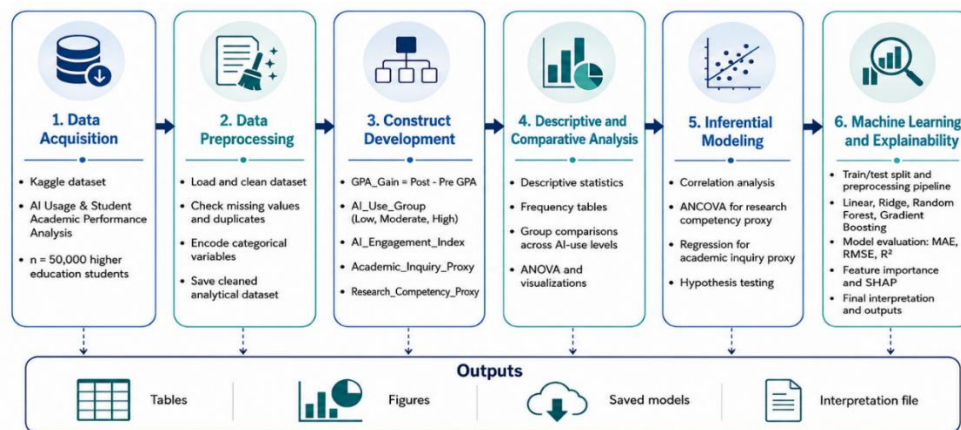


Figure 1. Python notebook-based analytical workflow for examining the role of artificial intelligence in research competency and academic inquiry development.

The workflow shows the sequence from dataset loading and cleaning to variable construction, group comparison, ANCOVA/regression analysis, machine learning prediction, feature importance, and final interpretation.

3.2 Dataset Source and Sample Characteristics

A publicly available data set was used for the study, which was the AI Usage & Student Academic Performance Analysis [21] data set from Kaggle. Data collected includes student-level data on use of generative AI, academic performance, study habits, prompt engineering skill, dependency on AI, institutional AI policy, exam anxiety, and skill retention. The end result analytical sample comprised 50,000 higher education students.

The dataset was suitable for the present study as it contained variables that were directly related to AI engagement and academic outcomes. While it did not include a standardised measure of research competency per se, it was possible to

identify several indicators that could be used to develop defensible proxy measures. These were: Weekly use of generative AI, prompt engineering skill, tool diversity, presemester GPA, postsemester GPA, GPA gain, and skill-retention score. The large sample size also ensured the reliable group comparison, regression modeling, and machine learning prediction.

One caveat of the dataset is that it is not directly possible to identify children or young people with disabilities or specific learning difficulties, or those with formal special educational needs. As such, the results should be viewed as evidence for inclusive higher education and for the use of AI to scaffold learning in the classroom, and not as evidence for a disability-specific outcome.

3.3 Variable Operationalization and Construct Development

AI engagement was measured as follows: Weekly GenAI hours, Prompt-engineering skill and Tool diversity. These dimensions were measured as weekly hours of GenAI usage, skill in prompt

engineering, and variety of learning behaviors using AI tools. We used tertile grouping of the weeks' AI usage to classify the students into low, moderate, and high usage groups.

Academic development was measured using the post semester GPA and GPA gain. GPA gain was the difference between the pre- and post-semester GPAs. To minimize the effect of prior academic achievement, the baseline control variable pre-semester GPA was used.

A Constructed Research Competency Proxy was used to operationalize competency in research. Skill retention, post-semester academic performance, prompt-engineering skill and diversity of tools were incorporated into this composite indicator. The selected components reflect the key areas of research competency in higher education, which include knowledge retention, academic performance, knowledge-seeking capabilities and the strategic use of learning tools, and the ability to engage with AI supported information system.

Academic inquiry skill was operationalized by using Academic Inquiry Proxy. This construct was a combination of skill retention, prompt-engineering skill, and post-semester GPA. The reasons for this were that academic inquiry involves sustained learning, questioning, information handling and academic reasoning. Prompt-engineering skill was added because the ability to pose clear, focused and evaluative questions is becoming a critical skill for effective use of AI.

The control variables were traditional study hours, perceived dependency on AI, exam anxiety, pre-semester GPA, major category, year of study, institutional policy, and burnout risk level. These variables were added to account for effects of AI beyond academic and psychological.

3.4 Data Analysis Procedure

Data screening involved an examination of missing values, duplicate values, type of variables, and distributional properties, as needed to begin the analysis. Pre-semester GPA, post-semester GPA, weekly GenAI hours, traditional study hours, GPA gain, skill-retention score, AI

engagement index, academic inquiry proxy, and research competency proxy were then calculated as descriptive statistics, for all key numerical data.

Then, comparisons were made between the low, moderate and high AI use groups at the group-level. Mean differences were compared between the groups for GPA gain, skill retention, academic inquiry proxy, research competency proxy, perceived AI dependency and exam anxiety. A one-way ANOVA test was used to test whether the differences in outcomes between the AI-use groups were statistically significant.

The strength and direction of the relationships among the AI engagement variables, GPA gain, skill retention, and each of the academic inquiry and research competency proxies, as well as the relationships among the AI engagement variables and perceived AI dependency were then analyzed using correlation analysis. This is the first step that gave an idea of the link among academic and competency-related measures to indicators of academic and competency-related behaviors related to AI.

ANCOVA and multiple regression models were estimated to increase the inferential evidence. With the pre-semester GPA, weekly GenAI hours, prompt-engineering skill, tool diversity, traditional study hours, perceived AI dependency and examination anxiety as ANCOVAs, the primary ANCOVA model predicted the Research Competency Proxy. This model was key for the study as it examined if the influence of the AI-related variables was independent of the baseline academic performance and study-related controls.

3.5 Model Evaluation and Explainability Framework

Machine learning models were designed to predict the Research Competency Proxy, and to explore which student-level factors had the strongest association with the AI-supported academic skill development. To test the four predictive models, the models were tested; Linear Regression, Ridge Regression, Random Forest Regression and Gradient Boosting Regression. They divide the data in two parts: A training set and a testing set, and then they preprocess the

data by imputing missing values, scaling the numerical values and one-hot encoding the categorical values. In this way, both numerical and categorical indicators were made available for the modeling process such as the study behavior, the use of AI, the presence of institutional policy, and learner background variables.

The mean absolute error, root mean squared error, and coefficient of determination were used to evaluate model performance. To make sure the models were stable and not relying on just a one train-test split, cross validation was used. This best-performing model was selected using accuracy metrics about the predictions with R^2 and error-based metrics given special importance. However, the only measure of the methodological value used was predictive accuracy. It was also important to consider the interpretability of the model in the context of inclusive and special education: educational models should enable transparent decision-making processes, not be opaque technical systems. To determine the most powerful predictors of the developing of competences in research, model explainability was therefore introduced. As the explainability method, permutation feature importance was chosen as the main method due to its ability to estimate the relative contribution of each predictor to model performance. An additional interpretability procedure employed was Random Forest feature importance and SHAP analysis. The skills practiced, number of times learners used AI, how well they could write prompts and instructions, their use of a range of tools, their traditional knowledge of studying, institutional policy, the learners' sense of relying on AI and their anxiety

were examined to determine the extent to which they predict research competency.

AI learning interventions need to be assessed not only for effectiveness and efficiency but also for pedagogical transparency, accessibility and equity, which is particularly significant for inclusive higher education. Research competency predictors can help educators understand which types of AI engagement might be conducive to academic inquiry and what might signal research dependency, anxiety or inequity in relation to others. This is crucial in creating an AI-enabled academic context that is responsive to different learners, including individualized academic support. The nature of the data and secondary data renders the study non-randomized where the causal effect of the study is not claimed. Rather, it offers proof of connections, prediction, and explainable modeling patterns between AI engagement and growth of research competency as well as academic inquiry in higher education. Rather than serving as causal evidence of the impact of AI related learning behaviors on inclusive learning of academic skills, these are interpreted as evidence of their effects as they may serve to support and/or impede such learning.

4. Results

4.1 Dataset Profile and Variable Operationalization

This section presents the analytical structure of the dataset and explains how the main study variables were operationalized. Because the dataset did not include standardized scales for research competency or academic inquiry, proxy indicators were constructed to represent these concepts in measurable form.

Table 1. Dataset variables and operational definitions

Variable	Type	Role in study	Operational definition
Weekly_GenAI_Hours	Continuous	Independent variable	Number of hours per week students reported using generative artificial intelligence tools.
AI_Use_Group	Categorical	Grouping variable	Students categorized into low, moderate, and high AI-use

			groups based on weekly GenAI use.
Prompt_Engineering_Skill	Categorical	Independent variable	Student-reported level of skill in constructing effective AI prompts.
Prompt_Engineering_Skill_Num	Numeric	Independent variable	Numeric encoding of prompt-engineering skill for statistical modeling.
Tool_Diversity	Continuous / ordinal	Independent variable	Breadth or number of AI tools used by the student.
Traditional_Study_Hours	Continuous	Control variable	Number of hours spent on conventional study activities.
Pre_Semester_GPA	Continuous	Control variable	Baseline academic performance before the semester.
Post_Semester_GPA	Continuous	Outcome variable	Academic performance after the semester.
GPA_Gain	Continuous	Outcome variable	Difference between post-semester GPA and pre-semester GPA.
Skill_Retention_Score	Continuous	Outcome variable	Score representing students' retained learning or competency level.
AI_Engagement_Index	Continuous	Constructed predictor	Composite index combining weekly GenAI use, prompt-engineering skill, and tool diversity.
Academic_Inquiry_Proxy	Continuous	Constructed outcome	Proxy measure representing academic inquiry skill development.
Research_Competency_Proxy	Continuous	Main outcome variable	Proxy measure representing research competency development.
Perceived_AI_Dependency	Continuous / ordinal	Control / risk variable	Student-perceived dependency on artificial intelligence tools.
Anxiety_Level_During_Exams	Continuous / ordinal	Control variable	Reported anxiety level during examinations.

Table 1 provides a summary of the independent, control, outcome and constructed indicators used for analysis. Artificial intelligence engagement was depicted in the weekly GenAI hours from engagement, AI-use groups, AI skill of prompt-engineering, a new GenAI tool diversity, and AI engagement index. The academic outcomes measured include post-semester GPA and level of GPA gain. The competency outcomes measured included the skill-retention score as

well as the Academic Inquiry Proxy and Research Competency Proxy.

The Research Competency Proxy was built on the following: skill retention, post-semester GPA, prompt-engineering skill and tool diversity. Academic Inquiry Proxy was built based on post-semester academic performance, skill retention and prompt engineering skill. This enabled the researchers to investigate the potential linkage between AI-in enabled learning behaviors and

superior higher order academic outcomes. This operationalisation is especially relevant to the context of inclusive higher education, as research competency and academic inquiry do not just

exist in the form of a score, but in terms of continuous learning, managing information, asking questions, and using academic resources strategically.

Table 2. Descriptive statistics of key study variables

Variable	N	Mean	SD	Min	25%	Median	75%	Max
Pre_Semester_GPA	50,000	3.146	0.479	1.183	2.834	3.210	3.521	3.998
Weekly_GenAI_Hours	50,000	8.428	8.269	0.000	2.390	5.800	11.720	40.000
Traditional_Study_Hours	50,000	11.209	5.156	1.000	7.560	11.180	14.710	35.860
Perceived_AI_Dependency	50,000	3.505	1.821	1.000	2.000	3.000	5.000	10.000
Anxiety_Level_During_Exams	50,000	4.271	2.144	1.000	3.000	4.000	6.000	10.000
Post_Semester_GPA	50,000	3.349	0.496	1.000	3.024	3.421	3.749	4.000
Skill_Retention_Score	50,000	75.798	13.282	10.780	66.820	76.000	85.190	100.000
GPA_Gain	50,000	0.203	0.187	-0.924	0.087	0.204	0.325	1.008
AI_Engagement_Index	50,000	0.000	0.688	-1.223	-0.566	-0.041	0.509	2.347
Academic_Inquiry_Proxy	50,000	74.718	11.642	19.973	66.247	74.333	83.208	100.000
Research_Competency_Proxy	50,000	73.748	11.113	20.479	65.578	73.320	81.959	100.000

Table 2 presents the descriptive statistics for the main numerical variables. The dataset included 50,000 higher education students. The mean pre-semester GPA was 3.146, and the mean post-semester GPA was 3.349, indicating an average GPA gain of 0.203. Students reported a mean of 8.428 weekly GenAI hours and 11.209 traditional study hours. The mean skill-retention score was 75.798. The mean Academic Inquiry Proxy was 74.718, while the mean Research Competency Proxy was 73.748. These results show sufficient variation in AI engagement, academic performance, and competency-related outcomes

to support comparative, inferential, and predictive analyses.

4.2 AI-Use Group Comparison

This is a comparison among students using generative AI weekly at low, moderate and high levels. The study aimed to find correlations between the various levels of exposure to AI and academic development, skill retention, outcomes related to the study and inquiry in relation to AI, research competency, AI-dependency, and anxiety.

Table 3. Comparison of outcomes across AI-use groups

AI-use group	N	AI hours	Pre-GPA	Post-GPA	GPA gain	Skill retention	Inquiry proxy	Competency proxy	AI dependency	Anxiety
Low AI use	16,694	1.571	3.147	3.337	0.190	75.797	74.511	73.528	2.534	3.822
Moderate AI use	16,642	5.966	3.145	3.364	0.219	76.850	75.310	74.258	3.118	4.005
High AI use	16,664	17.756	3.147	3.347	0.200	74.749	74.334	73.459	4.865	4.986

Table 3 shows that the low AI-use group reported an average of 1.571 weekly GenAI hours, the moderate AI-use group reported 5.966 hours, and the high AI-use group reported 17.756 hours. Pre-semester GPA was nearly identical across the

three groups, with means of 3.147, 3.145, and 3.147, respectively. This indicates that the groups were broadly comparable in baseline academic performance.

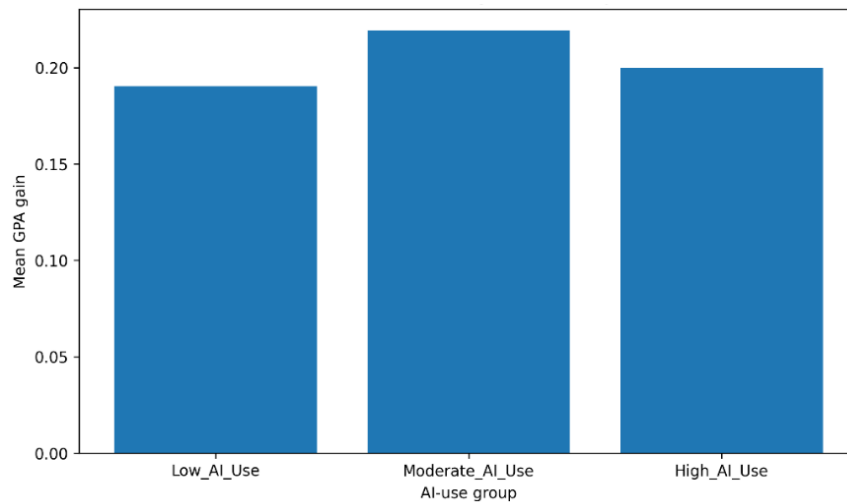


Figure 1. Mean GPA gain across AI-use groups

As observed in Figure 1, the moderate AI group gained the most in their GPA. The moderate group had a mean GPA gain of 0.219, the low AI-use group had a mean GPA gain of 0.190, and the

high AI-use group had a mean GPA gain of 0.200. The moderate use of AI was correlated with higher academic growth compared to minimal or intensive use of AI.

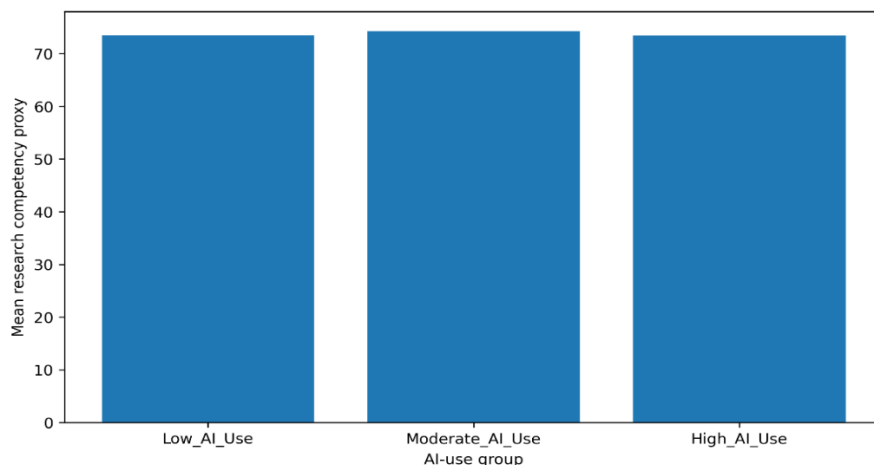


Figure 2. Research competency proxy across AI-use groups

The mean Research Competency Proxy scores for AI-use groups are shown in Figure 2. Moderate AI-users had the best performance with a mean score of 74.258 again. The low AI-use group had an average score of 73.528, and the high AI-use group had an average score of

73.459. While the numerical figures are relatively small, the trend is significant in the educational context as it implies that moderate usage of AI can be beneficial for the learning process without replacing independent investigation.

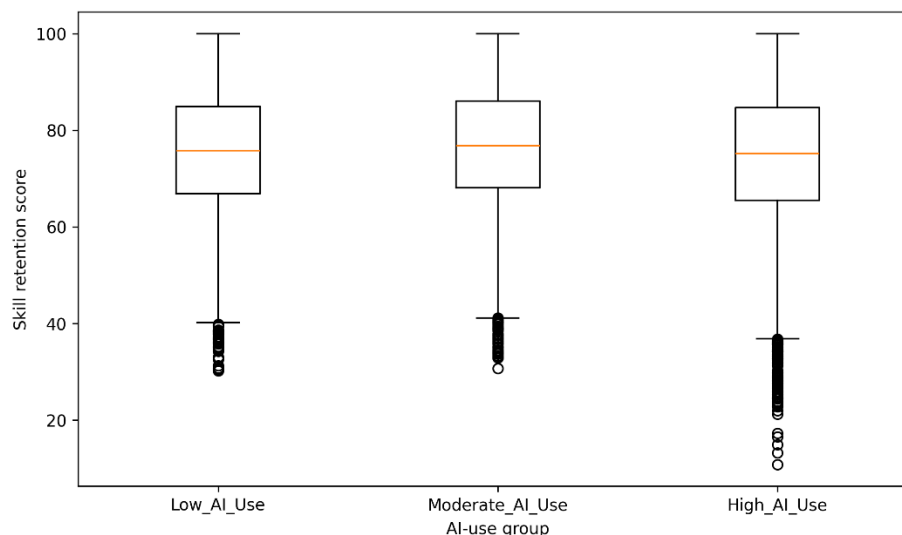


Figure 3. Skill retention score distribution across AI-use groups

The distribution of skill-retention scores for the three groups using AI is illustrated in Figure 3. The skill-retention score for the moderate AI use group was the highest at 76.850. The low AI-use group's score was 75.797, while the high AI-use group's score was 74.749. This result does not necessarily mean that higher AI exposure led to greater learning retention. This is significant from an inclusive education perspective to promote learning independence and retention, and not dependence on supporting technologies.

The group comparison in this study also revealed that as they used AI more intensely, they felt more dependent upon and anxious about exams.

The high-use group had a higher level of dependency on AI than the low-use group, with scores increasing from 2.534 to 4.865. The same groups reported higher anxiety scores (3.822 to 4.986). The results could indicate dependency and psychological risks with using AI on an intensive basis, particularly when used without academic support.

4.3 Correlation Analysis of AI Engagement and Competency Indicators

This section examines whether AI-use intensity or the quality of AI engagement was more strongly related to competency-related outcomes.

Table 4. Correlation matrix of AI engagement and competency indicators

Variable	WGH	PS	TD	AEI	GG	SR	AIP	RCP	AID
Weekly GenAI hours	1.000	0.019	0.008	0.498	- 0.046	- 0.118	- 0.061	- 0.052	0.665
Prompt skill	0.019	1.000	0.602	0.786	0.127	0.327	0.769	0.778	0.007
Tool diversity	0.008	0.602	1.000	0.780	0.081	0.197	0.463	0.605	0.006
AI engagement index	0.498	0.786	0.780	1.000	0.079	0.197	0.567	0.645	0.329
GPA gain	-0.046	0.127	0.081	0.079	1.000	0.196	0.258	0.265	- 0.039
Skill retention	-0.118	0.327	0.197	0.197	0.196	1.000	0.802	0.733	- 0.084
Academic inquiry proxy	-0.061	0.769	0.463	0.567	0.258	0.802	1.000	0.980	- 0.048
Research competency proxy	-0.052	0.778	0.605	0.645	0.265	0.733	0.980	1.000	- 0.040
AI dependency	0.665	0.007	0.006	0.329	- 0.039	- 0.084	- 0.048	- 0.040	1.000

Table 4 shows that weekly GenAI hours had a strong positive correlation with perceived AI dependency ($r = 0.665$). However, weekly GenAI hours had weak negative correlations with skill retention ($r = -0.118$), Academic Inquiry Proxy ($r = -0.061$), and Research Competency Proxy ($r = -0.052$). This indicates that time spent using AI alone was not associated with stronger competency outcomes.

In contrast, prompt-engineering skill showed strong positive relationships with Academic Inquiry Proxy ($r = 0.769$) and Research Competency Proxy ($r = 0.778$). Tool diversity was also positively related to Academic Inquiry Proxy ($r = 0.463$) and Research Competency Proxy ($r = 0.605$). The AI Engagement Index was positively correlated with Academic Inquiry Proxy ($r = 0.567$) and Research Competency Proxy ($r = 0.645$).

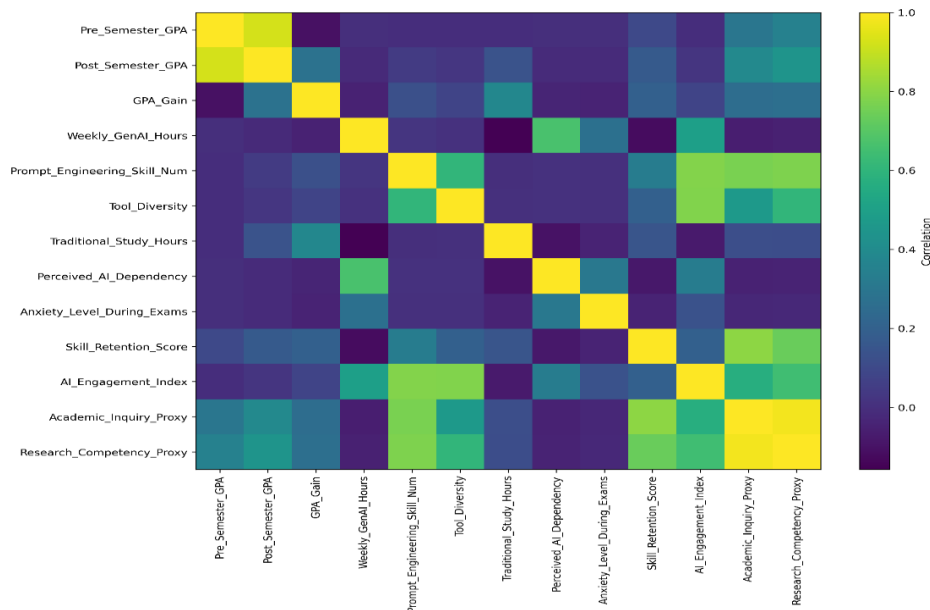


Figure 4. Correlation matrix heatmap

The findings in Figure 4 illustrate graphically that prompt-engineering skill and diversity of tools used were better associated with academic inquiry and research competency than would weekly hours using AI. The finding indicates that the effectiveness of academic development with the support of AI is more likely related to how it is strategically and skillfully used than to how often.

4.4 Inferential Analysis Predicting Research Competency

This section presents the main inferential model predicting the Research Competency Proxy while controlling for academic, behavioral, and psychological factors.

Table 5. ANCOVA results predicting research competency proxy

Source	Sum of squares	df	F	p-value
AI-use group	23,310.500	2	434.730	< .001
Pre-semester GPA	795,561.000	1	29,673.700	< .001
Weekly GenAI hours	23,682.800	1	883.347	< .001
Prompt-engineering skill	1,673,350.000	1	62,414.500	< .001
Tool diversity	180,134.000	1	6,718.840	< .001
Traditional study hours	74,341.200	1	2,772.860	< .001
Perceived AI dependency	10.956	1	0.409	.523
Anxiety level during exams	438.229	1	16.346	< .001
Residual	1,340,250.000	49,990	—	—

Table 5 shows that the ANCOVA model was statistically significant, $F = 20,030.000$, $p < .001$, and explained a substantial proportion of variance in research competency, with $R^2 = 0.783$. Prompt-engineering skill was the strongest predictor, $F = 62,414.500$, $p < .001$. Pre-semester GPA was also significant, $F = 29,673.700$, $p < .001$, indicating that baseline academic performance remained important. Tool diversity, $F = 6,718.840$, $p < .001$, traditional study hours, $F = 2,772.860$, $p < .001$, and weekly GenAI hours, $F = 883.347$, $p < .001$, were also significant predictors.

AI-use group was significant, $F = 434.730$, $p < .001$, showing that research competency differed

across AI-use levels even after controls. Perceived AI dependency was not statistically significant, $p = .523$, while anxiety level during exams was significant, $F = 16.346$, $p < .001$. Overall, the inferential findings suggest that AI-supported research competency is shaped less by exposure alone and more by prompt quality, diversified tool use, academic readiness, and sustained study behavior.

4.5 Predictive Model Performance and Explainability

This section reports the performance of machine learning models used to predict the Research Competency Proxy and identifies the strongest predictive features.

Table 6. Machine learning model performance

Model	MAE	RMSE	R ²
Gradient Boosting	3.904	4.839	0.812
Random Forest	4.058	5.043	0.796
Ridge Regression	4.079	5.080	0.793
Linear Regression	4.078	5.080	0.793

Table 6 shows that Gradient Boosting produced the strongest predictive performance, with MAE = 3.904, RMSE = 4.839, and $R^2 = 0.812$. Random Forest followed with $R^2 = 0.796$. Ridge Regression and Linear Regression produced

similar R^2 values of 0.793. These results indicate that the Research Competency Proxy could be predicted with relatively high accuracy, and that the non-linear Gradient Boosting model provided the best overall performance.

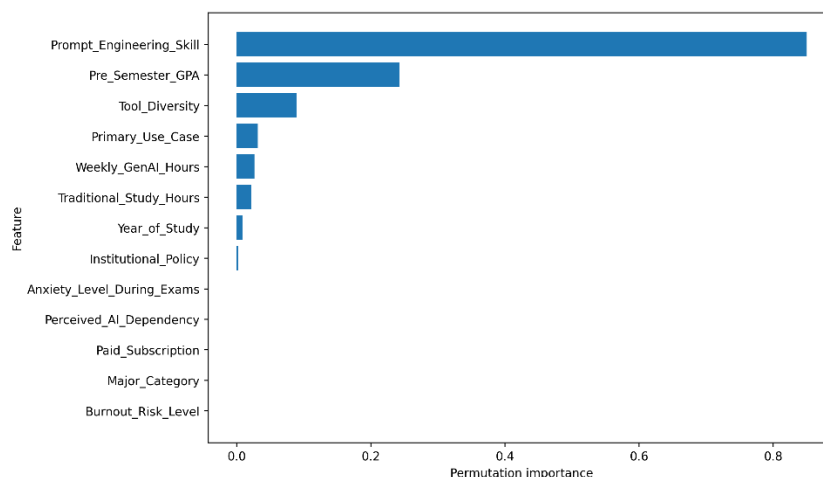


Figure 5. Permutation feature importance for research competency prediction

Prompt-engineering skill and pre-semester GPA were among the strongest predictors of research

competency, and more than pre-semester GPA, this skill was positively correlated with research

competency as shown in Figure 5. Other factors, such as weekly GenAI hours and traditional study hours, are of less significance. This finding further emphasizes the middle ground notion that the best thing students can do is use AI in a critical, strategic, and independent manner. Overall, the findings indicate that AI has a significant, but limited, impact on the growth of research competency and academic inquiry development. Moderate use of AI, robust prompt-engineering skill, diverse tools used, and traditional study engagement linked to better results. Exposure to high AI, however, was associated with increased dependency and anxiety. These findings point to the potential of using AI to assist students in learning rather than replace it – perhaps as a guided academic "scaffold" rather than a standalone source of knowledge.

5. Discussion

The results show that artificial intelligence can be used to enhance research capabilities and research inquiry skills in higher education, however, the usefulness of artificial intelligence depends on the quality and purpose of the interaction between students. The findings were far from clear-cut in terms of a "more is more" conclusion about the use of AI. However, students in the moderate AI-use group experienced the greatest increases in GPA, skill-retention score, academic inquiry proxy, and research competency proxy. The idea that AI can be more educationally helpful when it acts as a scaffolding tool for students in learning activities like inquiry, planning, revision, feedback, and academic reasoning, rather than replacing their own learning, is important. This is particularly applicable to the inclusive and special education setting. AI tools, which assist students with disabilities, specific learning challenges, language barriers, academic-literacy needs, and neurodiverse profiles in understanding, organizing, drafting, revising, and accessing academic material, can be beneficial. The high AI-use group also reported higher perceived dependence and anxiety, however. This suggests that the use of AI in education could pose potential hazards if students use it primarily

without being taught to critically evaluate, author, manage their learning processes and adhere to ethical standards. The support technology for diverse learners should enhance learner autonomy and participation and not establish new dependency relationships. This is also confirmed by the statistical results. The weekly GenAI hours had weak negative relationships in the skill retention, academic inquiry proxy and research competency proxy. Prompt engineering skill and tool diversity, however, were more strongly positively associated with competency measures, as were the AI engagement index. The ANCOVA model further indicated that academic performance at the beginning of the school year was the next strongest predictor of research competency after prompt-engineering skill, with tool diversity, traditional study hours and using GenAI weekly following. The question is not if a student uses AI, but how they use AI. The focus is no longer on whether students are using AI, but how. The results are aligned with previous studies indicating that for the purposes of education, AI should be considered in terms of pedagogical functions, challenges, and supports for students rather than simply a pedagogical tool [11]. They also are consistent with the larger body of research on AI in education indicating benefits for personalization, feedback, assessment, and learning analytics, while the benefits are realized through meaningful teaching integration [12]. The results corroborate the findings of the previous studies [13] on chatbot research, which highlight the role of AI as both a learning assistant and a potential risk if the students are not critical when using the bot. Focusing on inclusive education, these results concur with work in the field of equity-oriented AI that states that AI systems need to be designed to account for learner diversity, fairness, access, and impact [16]. The key takeaway is that AI can be incorporated into higher education in a pedagogically inclusive fashion. The use of AI for research methods training, academic writing support, disability services, and learning-support services should be integrated. Students will need to learn how to ask appropriate questions to AI, how to check and contrast AI sources, how to cite appropriately, and how to maintain their own

critical thinking in academic work. AI tools must be connected to Universal Design for Learning (UDL) with more than one way to access, represent, express and provide feedback on the content. There are a few things I should mention that are a limitation. Firstly, the study relied on a secondary observational data source, thus the results were of association and prediction rather than causality. Second, the data set was not composed of direct measures of research competency or academic inquiry but rather needed to be proxied. Third, this data set may not have distinguished between students with disabilities, specific learning difficulties and formal special educational needs, so the results should be treated as higher education evidence and not as disability-specific outcome evidence. Fourthly, there is a possibility of reporting bias in the measures of self-reported use of AI and prompt ability. Longitudinal, experimental and/or mixed method designs have the potential to investigate structured AI supported interventions among students with disabilities and diverse learning needs in future research. Future research should incorporate validated inquiry measures, direct measures of research outputs, and accessibility related variables. Explainable AI, user-friendly design of interfaces, Universal Design for Learning and AI scaffolding with the help of a human person should also be investigated for how they enable equitable participation in research learning in higher education.

6. Conclusion

This study focused on the problem of the role of artificial intelligence in the development of research competence and learning inquiry skills in higher education, inclusive and special education. The study adopted a secondary quantitative

design with the use of a publicly available data set of 50,000 students attending higher education institutions. An analysis and workflow using Python notebook was followed, which consisted of data preprocessing, development of constructs, descriptive analysis, group comparison, ANCOVA, machine learning based prediction and explainable feature importance analysis. The results reveal that the use of AI is not necessarily positive the more frequently it is used. Students who used moderate AI reported the highest GPA gain, as well as the highest scores on the skill retention and academic inquiry proxy, and the research competency proxy. The skill of prompt-engineering, the variety of tools employed, the baseline academic achievement, and the traditional study time were more predictive of research competency than intensity of AI use. These findings indicate that the higher the level of AI use, the more individual participants felt they were dependent on AI and anxious, which may pose risks to academic independence if they rely on AI too much or without support. The study is a contribution in providing an empirical and explainable framework to model the development of the competency of academic inquiry and research through AI assistance. From the findings it is suggested that the implementation of AI for inclusive higher education should be guided and implemented accordingly with pedagogy that is ethical, accessible and learner centered. Its main restriction is the reliance on secondary, observational, and proxy measures of research competency and/or disability-specific variables, instead of standardized measures. Longitudinal and/or experimental designs with validated instruments of inquiry and samples of students with disabilities and diverse learning needs are recommended for future research.

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