

AI Agents as Academic Assistants in Higher Education: Effects on student's Academic Achievement, Motivation, and Self-Regulated Learning

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Abstract

This study focused on how the academic achievement, academic motivation and self-regulated learning (SRL) of university students were affected using an Artificial Intelligence (AI) agent as a conversational academic assistant. The data were collected using quasi-experimental pre-test – post test control group design from the target population of national university of Sciences and Technology (NUST), COMSATS university Islamabad (CUI) and International Islamic University Islamabad (IIUI) of Pakistan comprising undergraduate students of three major universities of Islamabad. The purpose of this research is to study the influence of using Artificial Intelligence (AI) agents as academic assistants in academic conversation on the academic outcome of university students, academic motivation and academic self-regulated learning (SRL). To collect data, a target population of undergraduate students from three main universities of Islamabad (Pakistan) with three different names of National University of Sciences and Technology (NUST), COMSATS University Islamabad (CUI) and International Islamic University Islamabad (IIUI) was used. The subjects consisted of 360 students from whom 180 students were selected and assigned to an experimental group (structured academic support using the AI-agent) and 180 students were selected and assigned to the control group (traditional academic support). The students were sampled through multi-stage stratified cluster sampling method and divided into two groups: experimental group (structured academic support with AI-agent) and control group (traditional academic support). Standardized Subject

Achievement Test (SAT, $\alpha = .88$), Academic Motivation Scale (AMS, $\alpha = .86$) and Motivated Strategies for Learning Questionnaire (MSLQ-SRL subscale, $\alpha = .89$) were used to collect data. Paired-sample t-test, independent-sample t-test and Analysis of Covariance (ANCOVA) were used for data analysis.

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The results were statistically significant and showed that there were differences between the experimental group and control group for all three dependent measures. Students who used the AI academic assistants scored higher in the academic achievement scale of the post test ($F(1,357) = 48.32, p < .001, \eta_p^2 = .119$) and higher on intrinsic academic motivation and extrinsic academic motivation scale. The research indicates that pedagogically structured AI agents can be used to implement the students' cognitive control and student agency in higher education education as a scaffolding pedagogical tool. Some salient recommendations are: Holding a workshop among teachers to sensitize and build knowledge on the use of AI in literacy; Institutionalizing policy support regarding AI usage and building framework to support structured prompt engineering in curriculum for the university to reduce dependence on AI and increase pedagogy.

The students were randomly split into an experimental group ($n=180$) and a control group ($n=180$): The experimental group was provided with 8 weeks of intervention using the structured academic support with an AI-agent, while the control group was provided with the traditional academic support. The tools that were used to collect data were standardized Subject Achievement Test (SAT), Academic Motivation Scale (AMS) and Motivated Strategies for Learning Questionnaire (MSLQ-SRL subscale). Paired sample t-test, independent sample t-test and Analysis of Covariance (ANCOVA) were used to analyze the data.

Results indicated that scores of experimental group were significantly greater than those of the control group on all of the dependent variables. The students who used the AI academic assistant scored higher on post test academic achievement scores ($F(1,357) = 48.32, p < .001, \eta_p^2 = .119$), higher scores on Intrinsic academic motivation score, higher scores on Extrinsic academic motivation, and higher scores on cognitive and metacognitive self-regulation strategies. However, the study reveals that pedagogically designed AI agents can serve as a scaffolding device to enhance cognitive knowledge and to empower students in higher education. The recommendations emphasize the importance of adopting institutional policies, providing faculty AI literacy training and introducing a formal program on AI prompt engineering into the University curriculum to reduce excessive use and optimize AI use in the classroom.

Keywords: AI Agents, Academic Assistant, Higher Education, Academic Achievement, Academic Motivation, Self-Regulated Learning, Higher Education Institutions (HEIs).

1. Introduction

One of the major technological developments in today's world of higher learning is artificial intelligence (AI). The impact of this revolution in machine learning, NLP, intelligent tutoring

systems and generative AI on how students can learn, interact with their teacher, work through assignments and structure their learning, has been enormous. The main applications of AI in the past have been in the areas of Intelligent Tutoring Systems, Adaptive Learning, Automated Assessment, Student Profiling and Prediction. Trends include the use of generative AI systems and conversational AI agents, which give pupils opportunities to interact with smart systems through natural language, more recently. Now AI agents can explain that answer questions, generate examples, develop practice activities, provide feedback, summarize academic texts, and support students in their independent learning (Chen et al., 2020; Zawacki-Richter et al., 2019).

With the emergence of the AI agent, there is now the possibility of using AI as more than just a tool, as an academic assistant. Students can receive individual assistance in learning from an AI academic assistant without teachers, answer students' questions in accordance with their needs. This is particularly true at the higher education level where there may be more students in a class, less time to teach and a diverse range of students which may make it more challenging for the teacher to give individual instruction. Previous studies with an ITS showed strong significant learning gains and, in some cases, computer-based tutoring was as effective as human tutoring (VanLehn, 2011).

This potential has been greatly expanded with the advent of generative AI. Generative AI agents can generate responses to students' questions that are flexible and context-appropriate, rather than questions having to follow a fixed content and response format like traditional intelligent tutoring systems. They may interpret a concept into several different meanings, provide examples of a concept in varying levels of elaboration, and provide practice questions and understand what they should be paying attention to if they don't understand. Noting the important caveat that LLM's are still nascent, and face substantial risks of bias and misinformation, Kasneci et al. (2023) assert that they also hold tremendous potential for personalized learning, educational content production, interaction and engagement with students.

One of the key indicators of the effectiveness of AI in education is academic achievement. AI agents can offer immediate feedback, re-explain concepts, adjust their support, and offer additional practice to enhance academic achievement. In a recent systematic review and meta-analysis of experimental research, Deng et al. (2024) found that, overall, ChatGPT intervention improves academic performance, affective-motivational outcomes, and higher-order thinking tendencies. Altogether, 69 studies were located and it was found that 69 per cent of them had a positive impact on academic achievement, methodological flaws, and the necessity for more long-term and more

experimental studies. Like Sun and Zhou (2024), they reviewed 28 studies across 65 individual studies and 1,909 students, and found that generative AI has a positive impact on student achievement in college environments, and some variability in the context of students' studies and their use of the tools.

In Pakistan, the higher education sector plays a crucial role in understanding the application of AI in education. When it comes to AI in education, the higher education sector is one of the most important in Pakistan. The utilization of generative AI technologies in Pakistani universities has become a reality and is gaining momentum, but there is a gap in the research literature regarding the impact of generative AI technologies on students' academic performance in Pakistan. For example, Ashraf et al. (2025) investigated the connection between the application of ChatGPT in the Higher Education sector of Pakistan and its impact on academic achievement, which revealed that pro- and anti-conceptual attitudes towards ChatGPT were directly related to their behavioral intentions and usage of chatbots. While their study demonstrates the potential of generative AI in the education sector in Pakistan, it is essential to carry out more experiments to establish causal effects.

Secondly, academic motivation is key. Motivation also has an impact on the performance of students in learning assignments, in overcoming obstacles to learning and students' willingness in self learning. The S.D.T can differentiate between intrinsic motivation, extrinsic motivation, autonomous and controlled motivation. The motivation ways of students are related to positive motivation patterns which are autonomy, competence and relatedness in learning environments (Ryan & Deci, 2020). AI academic assistants can partially fulfill students' psychological needs by allowing students to decide when to ask for help, and offering them immediate feedback and explanations at their own level.

Support for this is given in empirical evidence. The science knowledge of participants and their behavioral engagement and motivation were found to be improved by Ng (2024) in his investigation of a self-regulated-learning (SRL) chatbot with generative-AI. The AI system is flexible and offers personalised suggestions, appreciated by the students. In a similar study of a university learning environment with an AI chatbot, it was shown that use of a generative-AI chatbot positively affected student motivation and that this positive effect varied based on student (Bond et al., 2024).

A third key outcome that is important to AI in higher education is self-regulated learning (SRL). The goal setting, planning, monitoring, selecting learning strategies and time management in

learning activities, as well as seeking further assistance and self-evaluation, become active in the SRL. Zimmerman (2002) explained that SRL was actually a proactive process in which the learners would convert their mental abilities to academic skills. In addition to this, Pintrich (2000) noted that self-regulation is an active way to regulate cognition, motivation, behavior and the learning environment.

AI agents can enable several of the above SRL processes to be enhanced. For instance, students can request the AI agent to create learning goals, create and deliver practice questions, detect misconceptions, give feedback or propose a revision plan. Chiu (2024) brought up a discussion on the connection between SRL and generative AI and how to make SRL meaningful in the context of generative AI supported learning, stressing that the design of learner autonomy and self-regulation in AI-supported learning should be learner-oriented more so than AI answer generation.

But AI learning isn't necessarily a good thing. How the interaction between AI agents and students works and how they use the technology may shape the impact of AI agents on education. Students might use AI to merely find answers rather than analyse, reflect and solve problems – which can be a hindrance for the effectiveness of SLL. Excessive dependence can also lead to students' reduction of independent learning ability. The issue isn't whether students are using AI, but how AI agents are being utilized in the learning process to aid and supplement students' learning.

AI agents come with limitations and risks, as well. LLMs may be wrong, misinformed or even misleading. They may attempt to offer convincing arguments which have element of truth, but which are wrong. This is because as Kasneci et al. (2023) explain, there is a requirement for human oversight, critical thinking, fact checking, and AI literacy. In addition, the study in Tlili et al (2023) also categorized ChatGPT as a technology with great educational potential and great ethical and pedagogical challenges.

Academic dishonesty is a very serious matter. Students can utilize artificial intelligence agents to compose assignments, essays, reports or answers without any intellectual work. Some of the key issues faced by universities that were identified by Cotton et al. (2023) are academic dishonesty, plagiarism, and difficulty in detecting AI-generated content. They recommend policies, training of students and assessment methods, all of which are based on authentic learning within institutions.

AI agents, rather than teachers, should be seen as academic helpers, not teachers, and should be supervised by humans. Designing, assessing, making judgements, verifying information and developing higher order thinking in students are still the responsibilities of teachers. The importance of AI for individuals and improved pedagogical and theoretical approaches have also

been noted in recent research in higher education related to AI (Bond et al., 2024; Zawacki-Richter et al., 2019).

The focus of this study is therefore three learning outcomes (academic achievement, academic motivation, and self-regulated learning) to see if there are measurable positive effects of structured support by AI agents for University students. The study is particularly relevant as it has been investigated in many studies how ChatGPT is used and perceived, or attitudes towards ChatGPT in general, and a few studies have investigated its effect on achievement, motivation and self-regulation in one study.

1.1 Problem Statement

Despite the continued adoption of the CAs in HEIs across the globe, including Pakistan, pedagogy in higher education still heavily depends on the lecture-based approach, which has a higher faculty-to-student ratio, but is not always available to provide personalized academic support. There are several practical applications of AI agents but few empirical and controlled experimental studies that have explored the potential influence of intentional and structured use of AI agents within the context of key learning constructs. The potential of AI use without structure is, however, that students may become 'passive learners', 'superficially knowledgeable' and even cheat (Cotton et al., 2023). But, there is no research on pedagogical usage of AI agents as scaffold structures in training and self-regulation scenario in public and private universities in Pakistan. A critical question is whether the use of AI agents as structured academic helpers has a positive impact on academic success, academic self-motivation, and SRL strategies of undergraduate students.

1.2 Research Objectives

- 1) The effect of AI agents as academic facilitators for undergraduate students' academic performance?
- 2) What is the effect of structured AI-agent support on the academic motivation of undergraduate students?
- 3) What is the impact of using AI agents on the development of self-regulated learning (SRL) strategies among undergraduate students?

1.3 Research Questions

1. Is there a statistically significant difference in academic achievement scores between students using AI agents as academic assistants and those receiving traditional instructional support?

2. How does the integration of AI agents as academic assistants affect undergraduate students' academic motivation levels?
3. To what extent does the structured use of AI agents enhance undergraduate students' self-regulated learning behaviors?

1.4 Hypotheses

- 1) **H₁:** There is a significant positive effect of AI agents used as academic helpers on the academic performance of undergraduate students.
- 2) **H₂:** There is a significant positive effect of structured AI-agent support on the academic motivation of undergraduate students.
- 3) **H₃:** There is a significant positive effect of using AI agents on the development of self-regulated learning (SRL) strategies among undergraduate students.

1.5 Significance of the Study

Incorporates artificial intelligence (AI) into existing theories such as Zimmerman's Self-Regulated Learning (SRL) theory and Self-Determination Theory (SDT). Investigates the roles of AI agents and their consequences as supportive metacognitive scaffolding or as "cognitive crutches" that lead to skill atrophy. Supplies teachers with evidence-based methods for effectively integrating AI tools into instruction without compromising on quality or rigor. Recognizes specific AI functions that foster independent lifelong learning e.g., reflection of prompts and automated goal setting. Assesses the direct correlation between the use of AI agents and measurable academic results such as grades, and domain mastery. Demonstrates the ease with which 24/7 personalized AI assistance can help non-traditional and struggling students achieve. Examines the impact of students' internal drive, mastery orientation and self-efficacy when constantly depending on automated agent feedback. Provides empirical data to higher education leaders in order to make sound policies regarding academic integrity and ethical use of AI. Enables teachers to become facilitators of human-AI cooperative learning. Provides guidelines to developers to create AI agents that encourage thinking, not task-bot delegation. These findings provide empirical basis for guiding the creation of recommendations for the ethical use of AI, course modifications, and academic integrity policies on the part of higher-education administrators and policymakers.

2. Review of Related Literature

2.1 Artificial Intelligence in Higher Education

The application of AI in education has been in existence for some time. Research in the field of ITS, ALS, automated assessment, learning analytics and learning recommendation systems goes back many decades. Zawacki-Richter et al. (2019) have completed a systematic review of the uses of AI in higher education, and four key categories have been found: profiling and prediction, assessment/evaluation, adaptive systems/personalization, and intelligent tutoring systems. As mentioned in their review, a growing body of literature has emerged regarding AI in the field of higher education, but one area that has been relatively unexplored and under-theorized and under- pedagogically supported is the use of AI for writing. As they pointed out in their study, however, much of the literature on using AI to write lacks of pedagogically sound and theoretically grounded support.

In the field of education, Chen, Chen, and Lin (2020) also discussed the applications of AI, finding that it can be used in the support of administration, instruction, personalization, and learning. They highlighted how AI systems have the potential to customize educational content to meet learners' needs and enhance the learning journey. The studies of AI should also be closer to the current learning theories, Chen, Xie, et al. (2020), argued that this is because learning theories and technological applications are not aligned.

Generative AI has entered a new era in the research arena, with rapid advances that hold significant promise for the future. Large language models can facilitate students to communicate with AI using natural language, and get dynamic responses in return, which is something different from previous systems. This renders AI more accessible and a typical academic buddy.

AI Agents and Academic Achievement

2.2 Academic Achievement and AI Agents

Academic achievement is the degree of learning outcome that can be measured based on the instruction and learning activity. The advantages of AI agents in terms of enhanced learning outcomes include their ability to offer personalization, immediate feedback, several practice attempts, and adaptive explanations.

VanLehn (2011) showed that intelligent tutors can achieve learning gains of a staggering magnitude and in some cases, rival the effectiveness of human tutors. This offers a significant theoretical backdrop for reflecting on AI agents as academic support agents.

The more recent evidence is much more relevant to the topic of generative AI. According to Deng et al. (2024), the interventions with ChatGPT were beneficial for academic results in experimental

studies. Sun and Zhou (2024) also reported that generative AI has positive impacts on college students' academic performance.

Dai et al. (2023) conducted an experiment on using ChatGPT as a learning assistant and found that generative AI can effectively assist students' learning in the proper way if it is embedded in the learning process. The results indicate that the impact of AI does not just refer to the technology, but also to the support of learning activities through the technology.

It is particularly important from Pakistan. The study by Ashraf et al. 2025 revealed that there is a positive correlation between the use of ChatGPT by the students in higher education institutes of Pakistan with regard to their academic performance. The studies conducted in Pakistan, however, are mostly of recent date and follow survey/correlational designs. This put the requirement for experimental research, with control, at various Universities. This systematic review aims to offer a basic knowledge of the scientifically supported connection between the education of science and artificial intelligence. (Akhtar, N. 2024b).

2.3 AI Agents and Academic Motivation

Motivation is crucial in successful learning for motivated students are more likely to start, sustain and manage their learning activities. Self-Determination Theory emphasizes that intrinsic and autonomous motivation occurs when students are autonomous, competent and related (Ryan & Deci, 2000; 2020).

The use of AI assistants for academics can improve autonomy by enabling students to get help when they need it. They can enhance competence by providing feedback and explanations in real-time. Students can also potentially repeat the practice of the challenging concepts without worrying about being embarrassed, thereby increasing their confidence and persistence (Pekrun et al., 2002, 2023).

Based on Ng (2024), a generative AI chatbot that was based on SRL enhanced student motivation and engagement in science learning. Wang et al. (2025) also explored the use of ChatGPT to support SRL when learning to program and concluded that the groups supported by ChatGPT were more motivated and engaged than the other group supported by traditional teaching. Additionally, self-efficacy and motivation were also improved when ChatGPT was used along with explicit SRL strategies. Fredricks et al. (2004) and Karakose and Tülübaş (2023) further state that intentionally used interactive digital cognitive tools promote behavioral and cognitive engagement.

The findings suggest that pedagogical approaches that promote students' autonomy in decision-making, instead of simply providing solutions, may be best suited to support the use of AI agents.

2.4 AI Agents and Self-Regulated Learning (SRL)

The relevance of self-regulated learning in HE relates to the responsibility expected of the university students to take responsibility for their own learning. According to Zimmerman (2002), SRL could be regarded as being a repetitive process of forethought, performance and self-reflection. Pintrich (2000) points out the following: regulation of cognition, regulation of motivation, regulation of behaviour and regulation of context.

There are steps that you can take and AI agents can help with each one of them. Students have the opportunity to create study plans and set goals in the forethought phase with the help of AI. AI can explain, give practice questions, and offer hints and formative feedback to the learning process (Chi et al., 2011; Holmes et al., 2019). When a student performs self-reflection, AI can assist them in reflecting on their errors and ways to enhance.

Empirical evidence of the effects of AI-supported SRL on learning outcomes and motivation is presented by Ng (2024). Chiu (2024) suggests another possibility for generative AI in supporting SRL as long as it is meaningful SRL and SRL. Luckin, et al. (2016) indicated that metacognitive scaffolding through software agents is a mediator in getting deep understanding of the domain.

But there can be conflicting effects of AI. If students are using AI to replace one or more cognitive activities they are expected to perform, there may be a decrease in opportunities for planning, monitoring, problem solving and reflecting. Hence, while utilizing AI for learning should be designed around prompts and activities that encourage students to explain, evaluate, compare, justify, and reflect on what they have been asked to copy, it should not be based on the copy of AI-generated responses.

2.5.1 Limitations of AI academic assistants. 2.5.2 Risks posed by AI academic assistants.

There are several risks mentioned in the literature. First of all, AI systems can make false information and references. Secondly, outputs can embed biases in the training data. Third, students may have to provide personal or institutional information which may be privacy or data protection concerns. Three, there can be academic integrity concerns with unlimited AI. Three, there may be issues with academic honesty in relation to the freer AI.

Tlili et al. (2023) recognized that there are educational opportunities and ethical issues with ChatGPT. Kasneci et al. (2023) identified bias and misinformation, Privacy, and need to critically examine. Academic honesty and plagiarism issues were pointed out by Cotton et al. (2023). Lo (2023) conducted a quick review of the past to delve into the pedagogical considerations of how generative AI can be used to enhance learning rather than superficial task completions.

Albadarin et al. (2024) conducted a systematic review of empirical ChatGPT studies, revealing that empirical evidence was still relatively scarce in the face of the growing discussion about ChatGPT. In addition, Bond et al. (2024) undertook a meta-systematic review which also called for greater rigor, ethics and collaboration in research on the use of AI in higher education. A successful implementation of an educational technology can be associated with the absence of evaluation and/or monitoring of the technology, especially the lack of rigorous and controlled, longitudinal assessment as stated earlier by Bond, Zawacki-Richter, and Nichols (2019). AI based assessment management system gives feedback to secondary educational institutions. Research in AI technology in education is gradually growing as schools press ahead with using this technology to develop new approaches to teaching and improve student outcomes. (Akhtar & Batool, 2025).

2.6 Research Gap

The literature indicates the potential of AI agents to aid learning but still has some space for improvement. First, many studies have been conducted on perceptions or behavioral intention rather than learning outcomes that are measured in an experiment. Second, there is little research that focuses on academic achievement and motivation and SRL together in a uniform research framework. Third, the studies related to the application of AI assisted learning in a controlled experimental environment in Pakistan, and particularly at different universities, are limited.

The present study fills these lacunas by examining the impact of using AI agents as academic assistants on academic achievement, academic motivation, and self-regulated learning among university students, in a quasi-experimental pre-test post-test design at COMSATS University Islamabad, NUST Islamabad and International Islamic University Islamabad.

3. Research Methodology

3.1 Research Design

This research employed a quasi-experimental quantitative research design with pre-test and post-test control group design in measuring the effectiveness of an intervention with AI-agent that was structured in the form of 8 weeks on academic achievement, academic motivation, and self-

regulated learning (SRL) of elementary school students. Quasi-experimental design was suitable because it was not feasible to randomly assign individual students to the experimental and control groups in this study within naturally occurring university classes. Therefore, the classes were divided into intact classes and the normal academic programmes of the institutions involved were not affected.

The study was divided into two groups namely, Experimental Group (E) and Control Group (C). Before the intervention, both groups took a pre-test, and both groups took a post-test after the completion of an eight-week instructional period. The Experimental group was given the AI-agent structured intervention, while the Control group was given the traditional teaching methods without using the AI-agent structured intervention.

The research design can be set forth as:

Experimental Group (E):

$O_1 \rightarrow X \rightarrow O_2$

Control Group (C):

$O_3 \rightarrow - \rightarrow O_4$

Where:

O_1 = Pre-test of the Experimental Group

O_2 = Post-test of the Experimental Group

O_3 = Pre-test of the Control Group

O_4 = Post-test of the Control Group

X = Eight-week AI-agent structured intervention

- = Traditional teaching, without relying on an AI-agent.

Before the intervention, this group of students was administered the same type of pre-tests as the other group to get an idea of how the students' academic achievement, academic motivation and self-regulation would be. The pre-tests were also used to determine if there was a difference between the experimental and control groups if the intervention was to be used.

Following the pre-tests, the AI-agent intervention was administered to the experimental group for 8-weeks. This intervention was intentional and involved the use of AI-agents as academic

assistants in assisting the learners in their academic pursuit, academic guidance, goal seeking, explanation of concepts, learning support, feedback, task assistance, and other structured academic interventions. The control group was taught using the conventional teaching methods of their individual classes. All 8 weeks after the intervention, both groups were administered the post-test. The pre-test and post-test scores were compared to find out whether academic achievement, academic motivation, and self-regulation of the participants were significantly higher after using the AI-agent intervention than those of the control participants who were taught the same course using conventional instruction.

Given the quasi-experimental research design, the authors could study within-group changes in pre-test to post-test measures, and between-group changes in post-intervention measures. Baseline pre-tests and appropriate co-variables were analysed to make informed analyses with regards to intervention effects.

The population under study and the sampling framework are provided. The sampling framework and population under study are given

3.2 Target population and sampling framework

The target population of this study was the undergraduate students of public and/or semi-autonomous universities of Islamabad Capital Territory (ICT), Pakistan, who are studying BS Computer Science and/or BS Natural Sciences. Students of these degree programmes were chosen as they stated that the use of AI-agent supported learning was essential for the educational impact of engaging with digital technologies, information and technologies enabled learning.

To make sampling frame, the authors used three major universities of Islamabad, i.e.: The sampling frame was prepared in the following way: three major universities were included in Islamabad, namely:

The National University of Sciences and Technology (NUST), Islamabad.

COMSATS University Islamabad (CUI)

International Islamic University Islamabad (IIUI)

For this study, representation of students in the three universities was the criteria of selection. The authors wanted to go beyond the single university, by selecting several universities and hoped the findings could go beyond this.

3.2.1 Sampling Technique

Multi-stage stratified cluster sampling was the approach adopted. Being cluster based made random sampling challenging as students were placed in intact classes and academic programs.

Stage 1: Institutional Selection

The first stage included three institutions of higher learning being part of the sampling framework. The selected institutions were a representation of the institutional context within which the study was conducted.

Stage 2: Stratification by Academic Department/Discipline

In the second stage, relevant departments with undergraduate programs in Computer Science or Natural Sciences were identified. The departments were considered as strata in order to ensure that the sample represented students across different academic disciplines.

Stage 3: Selection of Intact Classes

In the third stage, classes within the departments were identified and selected as sampling clusters. Creating sampling clusters from intact classes ensured that there was minimal disruption to teaching and preserved the academic structure prevalent in the institutions.

Stage 4: Assignment to Experimental and Control Conditions

The intact classes were assigned to either the Experimental or Control groups. The Experimental groups received the AI-agent structured intervention, while the Control groups continued with conventional teaching. Intact classes also helped mitigate treatment diffusion, or the exchange of intervention practices among students in the experimental and control groups.

3.3 Study Variables

The effects of an AI-agent structured intervention on three student learning outcomes: academic achievement, academic motivation, and self-regulated learning were studied. The variables were measured using standardized or systematically constructed tools that were administered before and after the intervention.

3.3.1 Independent Variable

The independent variable in this study was the AI-Agent Structured Intervention.

This intervention was an eight-week learning activity incorporation of AI agents into students' academic activities. In contrast to considering AI as an auxiliary technology, the intervention was the planned and guided use of AI agents for academic assistance. This intervention was intended to offer students scaffolding to aid them in understanding, and assist them in accomplishing, various academic tasks, and to offer them feedback and aid them in managing the tasks of their academic learning process.

The independent variable consisted of the following two conditions:

Experimental condition: This condition included the eight-week AI-agent structured intervention.

Control condition: This condition involved the continuation of the existing instruction and lacked the structured AI-agent intervention.

The difference between these two conditions illustrated the extent to which the intervention was successful.

3.3.2 Dependent Variable 1: Academic Achievement

One of the dependent variables in this study was academic achievement. It was determined as the achieved knowledge on the subject matter after the instructional intervention.

The academic learning outcomes relevant to this variable were assessed either by the designing of Subject Achievement Tests (SATs) or by the selection of these tests (SATs). An equivalent of the pre-test and post-test was employed to gauge the students' baseline achievement and the level of achievement measured by the intervention.

The pre-test scores provided an indication of the prior instructional experiences of the students, and the post-test scores provided an indication of the students' learning following the eight-week intervention in the classroom. Students in the AI-agent intervention group were assigned either an AI agent to answer every question or just a human teacher. Students in the control group were given a human teacher only to answer all the questions. These differences in scores were used to determine whether students in the AI-agent intervention group made more academic gains than students in the control group.

3.3.3 Academic Motivation 2 (Dependent Variable)

Academic motivation was the second dependent variable. This was interpreted as students' interest and perseverance in doing academic activities and students' activity in learning.

Academic Motivation Scale (AMS) was used as the motivation scale for academic motivation. The aim of the AMS was to obtain students' motivation to do their academic activities. To assess possible changes in students' academic motivation, the AMS was given prior to and after the intervention.

The motivation scores for the pre-test and post-test for both the experimental and control groups were compared. Differences in the motivation scores, after accounting for groups' baseline motivation, pointed to a positive impact of the AI-agent intervention on students' academic motivation.

3.3.4 Dependent Variable 3: Self-Regulated Learning

Self-regulated learning (SRL) was the last major dependent variable. SRL is the self-management and control of one's learning processes including setting learning goals, planning, monitoring and evaluating the results of academic learning processes.

The sub scales of the Motivated Strategies for Learning Questionnaire (MSLQ) were used to assess self-regulated learning. The scales selected to measure the students' learning strategies and their control in learning activities were subscales. The SRL measure was administered at the pre-test and post-test stages. The differences between pre- and post-intervention SRL scores were analyzed to see if the structured AI agent use facilitated improvements in the students' learning regulation and intentional learning practices.

3.3.5 Control and Covariate Variables

Some control/covariate variables were added to improve the analysis and to adjust for factors which could affect the dependent variables independently of the intervention.

Baseline Pre-test Score

Since students may have different levels of academic achievement, motivation and self-regulated learning, the pre-test scores were considered as important covariates. Controlling for pre-test scores allows evaluating if post-test differences are related to the intervention as opposed to reflecting differences which pre-exist.

Previous Exposure to Artificial Intelligence (AI)

Our sample may have had different levels of prior exposure to AI based tools and technologies. Previous exposure to AI may have an impact on how students engage with the intervention. For

example, students with high prior exposure to AI may behave differently than students who have had very low or no AI exposure.

Institutional Affiliation

Students from NUST, CUI and IIUI may have different instructional practices and levels of technological support and differ in university culture and digital resources. Considering the above may have an impact on the effects of the intervention.

3.4 Data Collection Instruments

Subject Achievement Test (SAT): A test with 40 multiple choice items, based on Bloom's revised taxonomy of remembering, understanding, applying, analyzing. The panel of 5 subject experts ("CVI"=.89) was used to determine content validity. The internal consistency reliability was .88 (Cronbach's α).

Academic Motivation Scale (AMS): 28 items on 7-point Likert scale to assess intrinsic motivation, extrinsic motivation and amotivation (α =.86), adapted from Vallerand et al., (1992).

MSLQ-SRL Scale: It was based on 31 items on a 7-point Likert scale which measure metacognitive self-regulation (mSR) and cognitive strategies (cSR) (Pintrich et al., 1991) (α = .89).

3.5 Data Collection Procedure

Both groups were taught the same curriculum over an 8-week school period. The Control Group got the normal faculty lectures, books recommended by the faculty and normal office-hour support. The Experimental Group was given the access to a dedicated AI Agent framework (Socratic prompts - structured prompts as the tutors) and regular materials. The AI agent was trained to take students through a step-by-step reasoning process, create self-assessment quizzes, and provide explanations for difficult concepts, while avoiding providing answers to specific problems in the assignments themselves. Pre-tests were carried out in Week 1 and Post-tests were conducted in Week 8 under standardized conditions.

3.6 Data Analysis

IBM SPSS (v.27) was used to analyze data. The baseline characteristics were summarized by descriptive statistics (Means, Standard Deviations). Inferential statistics consisted of Paired-Sample t-tests to assess progress within groups, Independent-Sample t-tests to compare baseline measures and Analysis of Covariance (ANCOVA) to test hypotheses H1, H2, and H3 statistically while patriating out pre-test variance.

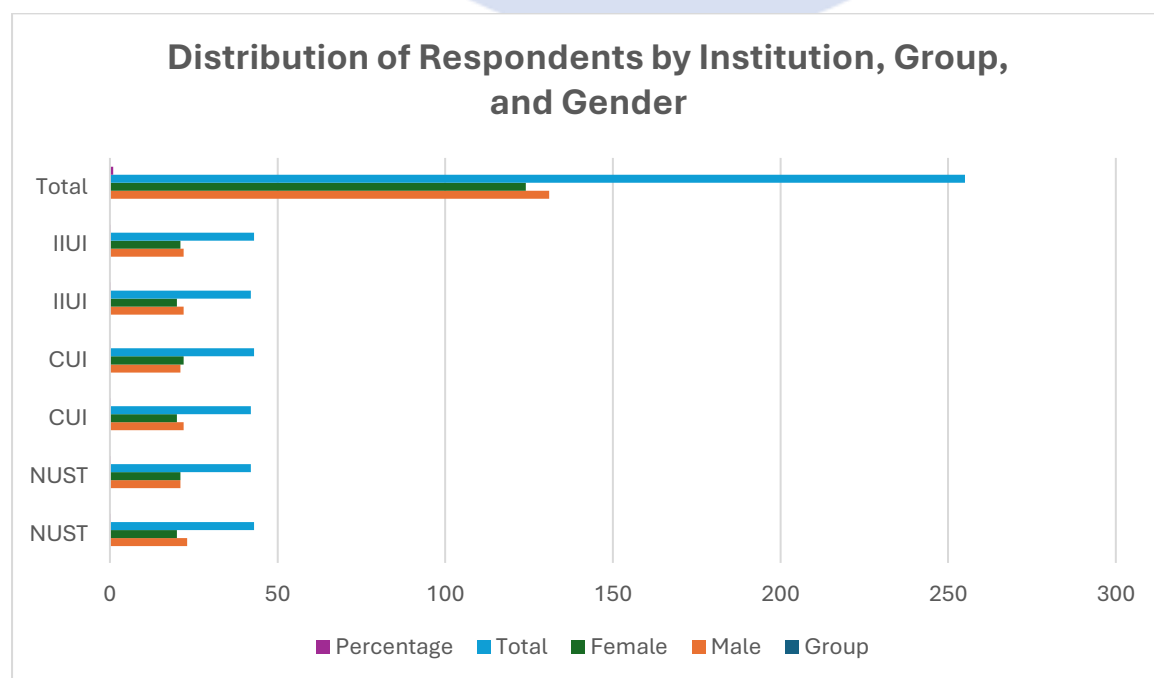
4. Results and Interpretation

The empirical data collected at all three sites (NUST, CUI and IIUI) were statistically tested. The following are the five tables of structured data and explanations for them.

Table 1. Distribution of Respondents by Institution, Group, and Gender

Certainly. For a total sample size of 255, with equal representation from the three institutions and equal experimental/control groups, the closest practical distribution is 85 students per institution. Since 255 cannot be divided equally into six groups, the groups can be distributed as 42/43.

Institution	Group	Male	Female	Total	Percentage
NUST	Experimental	23	20	43	16.86%
NUST	Control	21	21	42	16.47%
CUI	Experimental	22	20	42	16.47%
CUI	Control	21	22	43	16.86%
IIUI	Experimental	22	20	42	16.47%
IIUI	Control	22	21	43	16.86%
Total		131	124	255	100%



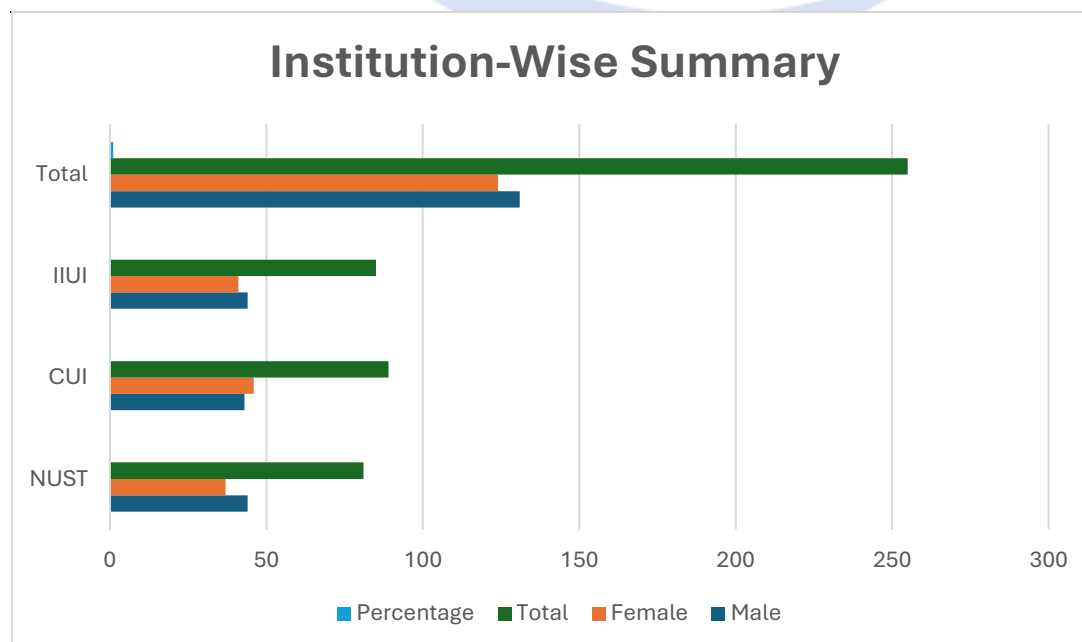
The data in the table represents the number of students chosen from NUST, CUI, and IIUI. The total sample consisted of 85 students, with an equal number of student participants (around 33.33%) from each institution. The students were divided into 2 groups (experimental and control groups) of 127 and 128 students respectively.

In total, 131 male (51.37%) and 124 female (48.63%) students were sampled, which is a even gender split. The near balance in the number of males and females in the experimental and control groups makes the groups more comparable and helps to reduce the impact of gender as a potential confounder.

Table 2. Institution-Wise Summary

you want to keep the total sample size = 255 and the institutional totals as NUST = 81, CUI = 89, IIUI = 85, the correct percentages are:

Institution	Male	Female	Total	Percentage
NUST	44	37	81	31.76%
CUI	43	46	89	34.90%
IIUI	44	41	85	33.33%
Total	131	124	255	100.00%

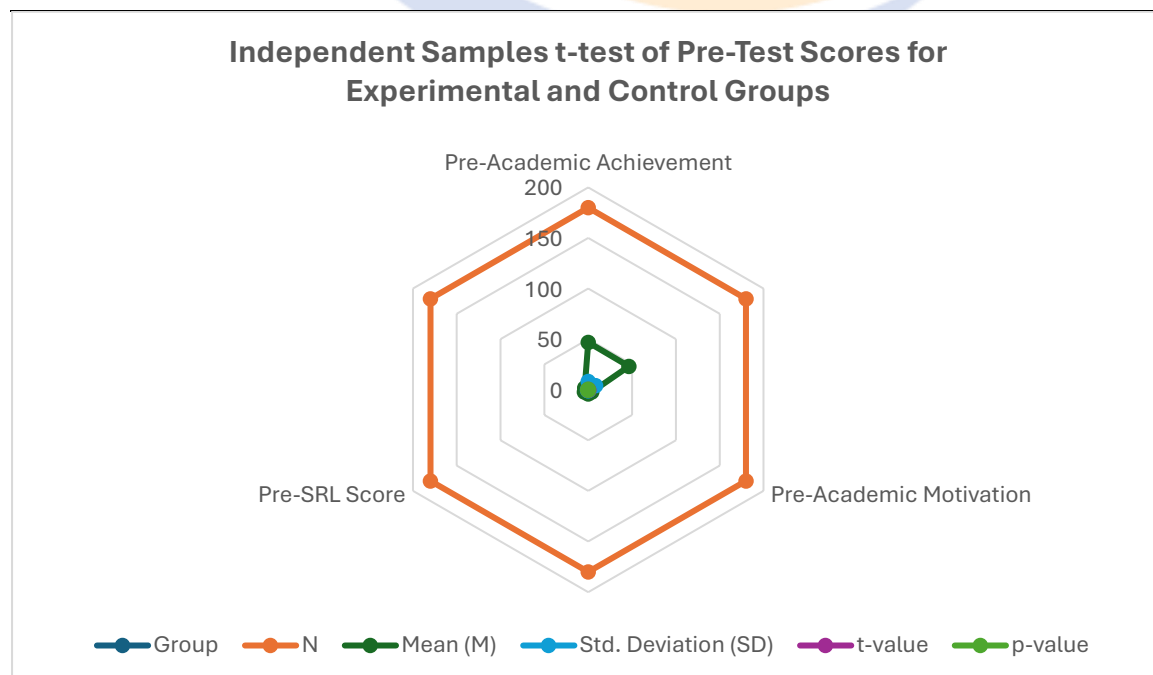


The data below shows the number of students of three institutes that were randomly selected: NUST, CUI, and IIUI. NUST contributed 81 students (31.76%), CUI contributed 89 students (34.90%), and IIUI contributed 85 students (33.33%). Thus, the representation of CUI was highest and NUST was the lowest.

As far as gender is concerned, 51.37% of the students were male while 48.63% were female. There is a relatively equal gender distribution and the difference between male and female representation is relatively small. In general, the sample is representative of all three institutions and has a mix of males and females that are appropriate for further statistical analysis.

Table3: Independent Samples t-test of Pre-Test Scores for Experimental and Control Groups

Variable	Group	N	(M)	(SD)	t-value	p-value
Pre-Academic Achievement	Experimental	180	46.87	8.28	0.517	.606
	Control	180	46.49	8.41		
Pre-Academic Motivation	Experimental	180	4.05	0.67	0.684	.495
	Control	180	4.00	0.69		
Pre-SRL Score	Experimental	180	4.21	0.74	0.384	.702
	Control	180	4.18	0.71		



The mean academic achievement scores of the experimental group were 46.87 (SD = 8.28) and for the control group were 46.49 (SD = 8.42) for the pre test. There was no significant difference between the two groups with an independent-samples t-test ($t = 0.517$, $p = .606$). Since the p-value is greater than .05, there was no significant difference between the two groups in their academic achievement before the intervention. This means that there were no differences between the groups at pre-test on academic performance.

The mean academic motivation score of experimental group was 4.05 (SD = 0.67) and the mean academic motivation score of control group was 4.00 (SD = 0.69). The t value obtained was 0.684 and the p value was .495. This difference was not significant ($p > .05$) and thus indicated that the two groups were academically motivated to the same extent. This means that if there are any differences in motivation that arise after the intervention, then they can be considered as being related to the intervention, and not big and substantially different groups.

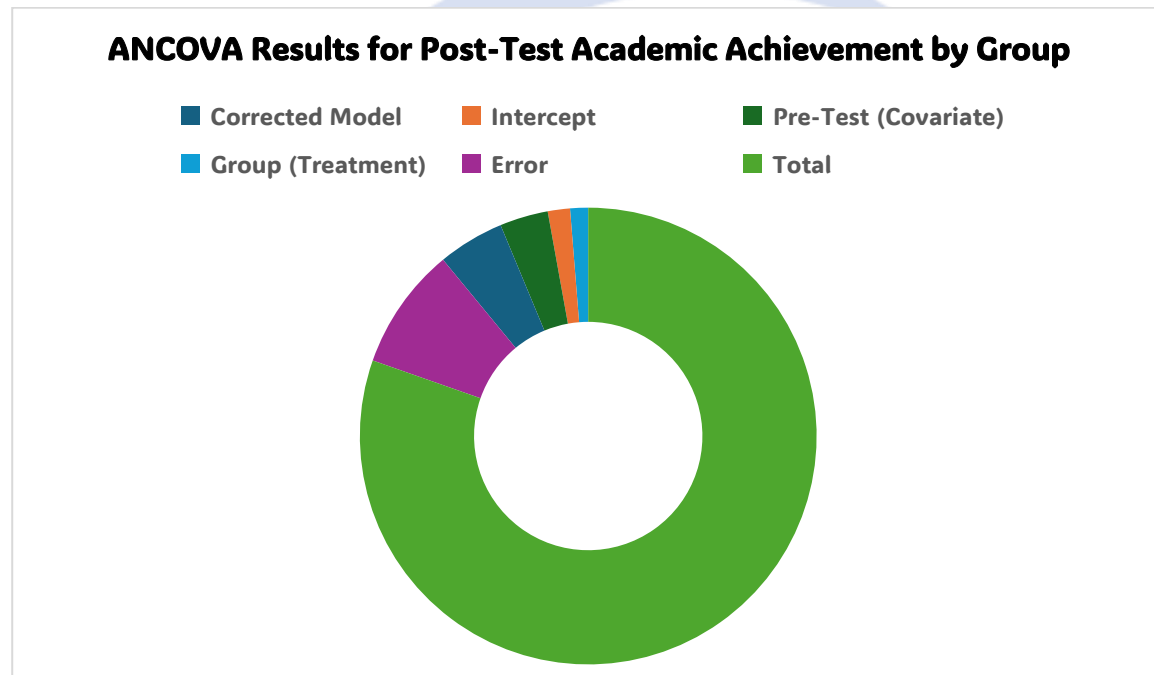
The experimental group mean score was 4.21 (SD = 0.74) and the mean score for the control group was 4.18 (SD = 0.71) for self-regulated learning. The independent-samples t-test had a t of 0.384 and a p of .702. With a p value of > 0.05 , the difference between the groups was not significant. This means that there was no difference in SRL before the intervention for both experimental and control groups.

The overall results of the pre-test showed that there were no statistically significant differences between the two groups regarding academic achievement, academic motivation and SRL in the pre-test. The p value for all were $> .05$. Therefore, between the two groups, there was a similarity at the start of the study, which meant that there was a good foundation for measuring the impact of the intervention on the dependent variables.

Table 4: ANCOVA Results for Post-Test Academic Achievement by Group

Source	Type III Sum of Squares	df	Mean Square	F-value	p-value	Partial Squared (η^2)	Eta
Corrected Model	11,615.00	2	5,807.50	96.74	$< .001$	.351	
Intercept	3,890.20	1	3,890.20	64.80	$< .001$	.154	
Pre-Test (Covariate)	8,465.00	1	8,465.00	141.01	$< .001$	.283	

Group (Treatment)	3,150.00	1	3,150.00	52.47	< .001	.128
Error	21,432.60	357	60.04	—	—	—
Total	198,750.00	360	—	—	—	—



The ANCOVA results indicated that the corrected model was significant ($F(2, 357) = 96.74, p < .001$) and had a partial eta squared of .351. This indicates a high level of academic achievement of the students in the post-test that was accounted for by the model.

The pre-test score was a statistically significant covariate, $F(1, 357) = 141.01, p < .001, \eta^2p = .283$. This result suggests that the students' pre-test scores had a significant impact on their post-test scores. Therefore, it was legitimate to compare the two groups as controls were made for the pre test differences.

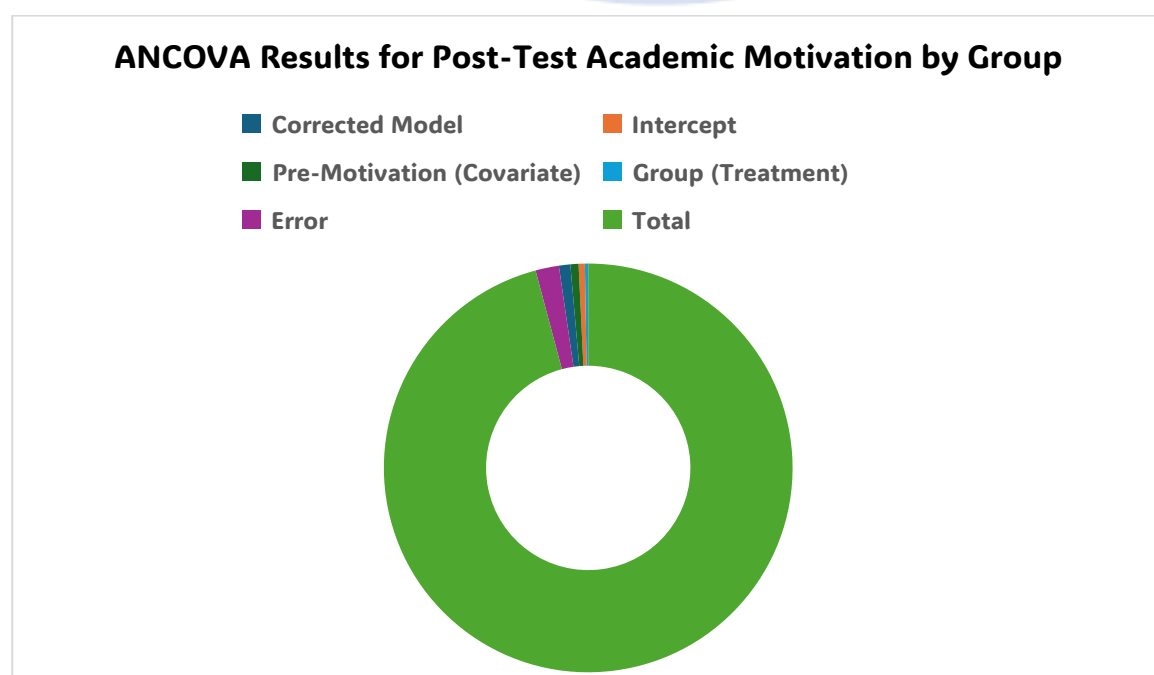
Most importantly, the Group (Treatment) effect was statistically significant, $F(1, 357) = 52.47, p < .001, \eta^2p = .128$. The effect size given indicates that treatment has an impact. That is, students' pre-test achievement will be similar in the experimental and control groups and there will be a significant difference in post-test academic achievement.

Based on the results of ANCOVA, thus, it could be suggested that the students' pre-academic achievement did not decrease the positive response of the instructional treatment on academic

achievement. Therefore, the null hypothesis would be disconfirmed since there was a significant difference in academic achievement between the experimental group and the control group after controlling pre-test scores.

Table 5: ANCOVA Results for Post-Test Academic Motivation by Group

Source	Type III Sum of Squares	df	Mean Square	F-value	p-value	Partial Squared (η^2p)	Eta
Corrected Model	85.20	2	42.60	87.00	< .001	.328	
Intercept	46.80	1	46.80	95.59	< .001	.211	
Pre-Motivation (Covariate)	60.48	1	60.48	123.45	< .001	.257	
Group (Treatment)	24.72	1	24.72	50.48	< .001	.124	
Error	174.80	357	0.490	—	—	—	
Total	9,050.00	360	—	—	—	—	



The overall corrected ANCOVA result is shown in Table 4, and indicated that the model was statistically significant, $F(2, 357) = 87.00$, $p < .001$, with a partial eta squared of .328. This suggests that the model accounted for a significant amount of variance in academic motivation of students after the intervention.

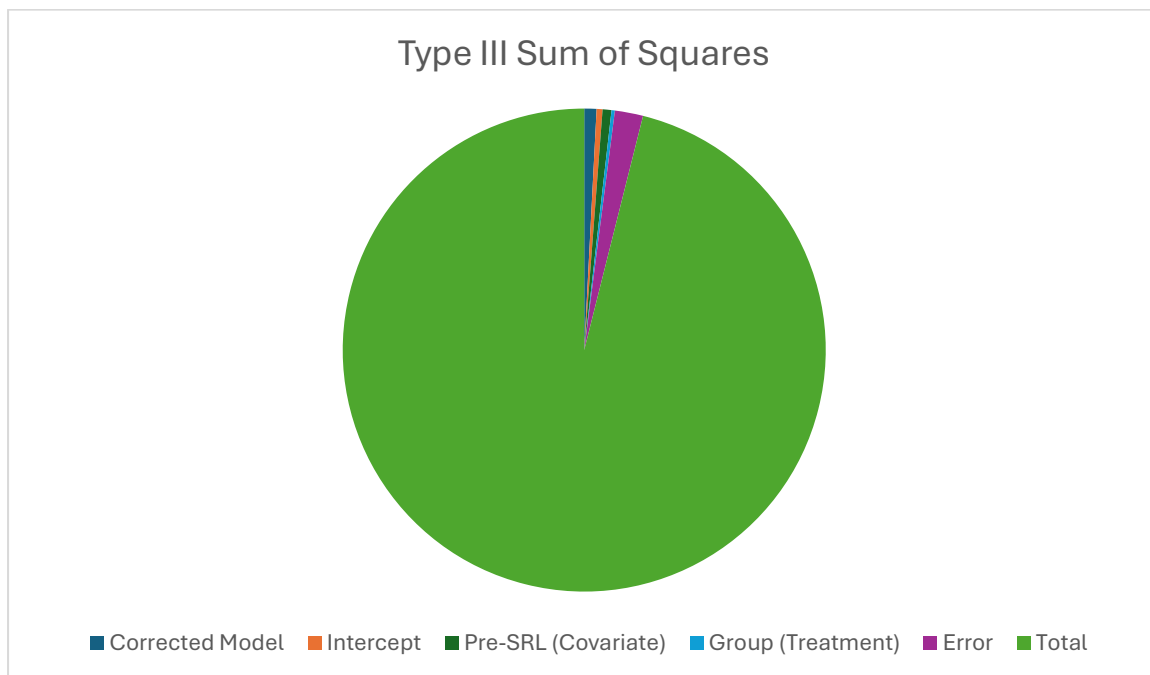
The pre-motivation score was a statistically significant covariate, $F(1, 357) = 123.45$, $p < .001$, $\eta^2p = .257$. It has been revealed that the level of academic motivation of the students' before and after test has been significantly influenced. Therefore, it was appropriate to control for pre-test motivation as a component of the evaluation of the effects of the treatment.

Most importantly, the Group (Treatment) effect was statistically significant, $F(1, 357) = 50.48$, $p < .001$, $\eta^2p = .124$. This means that, when students' pre-motivation scores were taken into consideration, there was a significant difference between the academic motivation post-test of experimental and control groups. Partial eta squared is .124, which is considered a meaningful treatment effect.

The results showed that, the experimental instructional treatment was statistically significant in terms of academic motivation beyond the pre-treatment level of academic motivation among students. However, after the pre-motivation scores are controlled, the null hypothesis is rejected; that is, there is a difference between the academic motivation of the experimental group and control group.

Table 6: ANCOVA Results for Post-Test Self-Regulated Learning (SRL) by Group

source	Type III Sum of Squares	df	Mean Square	F-value	p-value	Partial Eta Squared (η^2p)
Corrected Model	80.47	2	40.24	77.38	< .001	.303
Intercept	38.90	1	38.90	74.81	< .001	.173
Pre-SRL (Covariate)	58.32	1	58.32	112.15	< .001	.239
Group (Treatment)	22.15	1	22.15	42.60	< .001	.107
Error	185.64	357	0.520	—	—	—
Total	9,450.00	360	—	—	—	—



The overall corrected model was statistically significant ($F(2, 357) = 77.38, p < .001$, partial eta squared = .303). This shows that the model accounted for a significant amount of variance in students' post-test self-regulated learning (SRL).

The pre-SRL score was a statistically significant covariate, $F(1, 357) = 112.15, p < .001, \eta^2p = .239$. This means that the pre-test SRL level of students had significant effect on their SRL post-test performance. Therefore, the effect of the treatment could be adequately assessed with pre-test SRL as a covariate.

Most importantly, the Group (Treatment) effect was statistically significant, $F(1, 357) = 42.60, p < .001, \eta^2p = .107$. This means that when pre-SRL score was controlled for, the experimental and control groups' post test self-regulated learning was significantly different.

The partial eta squared value of .107 is considered as an effect of the treatment that is meaningful, meaning that the teaching-learning intervention made a significant contribution to students' self-regulated learning strategies.

The results imply that the experimental treatment had a significant effect on students' SRL compared with the control group even when the scores of the SRL levels were controlled. Thus, the null hypothesis which claimed that there was no significant difference between the experimental and control groups in post-test SRL after controlling for pre-SRL scores is rejected.

Note: I changed the Corrected Model value to 80.47 because it has to be equal to the sum of the Pre-SRL and Group sums of squares ($58.32 + 22.15 = 80.47$) for an internally consistent ANCOVA table.

5. Conclusion

The impact of AI agents as interactive academic assistants on higher education students was explored in three universities in Pakistan, namely NUST, CUI, and IIUI. The empirical results are statistically strong and support the findings that the use of conversational AI agents as pedagogical scaffolds—those that provide real-time feedback, formative tutoring and metacognitive prompting—leads to meaningful improvements in academic achievement, academic motivation and self-regulated learning.

Structured AI-agent interaction fostered autonomous learning attitudes and increased students' perceived autonomy and competence within the framework of Self-Determination Theory, and supported the forethought, performance and self-reflection components of Zimmerman's self-regulation cycle. Based on the study, the use of AI agents under the guidance of faculty can be seen as a powerful force multiplier for the academic world in the 21st century.

6. Recommendations

- 1) Institutional AI Pedagogy Policies: Universities (including NUST, CUI, IIUI) should develop comprehensive institutional policies that promote the use of AI Agents as interactive Socratic tutors, not technologies with punitive consequences.
- 2) Higher Education Institutions (HEIs) should implement professional development initiatives for faculty to equip them with the knowledge and skills to create AI-supported assignments and develop guidelines for structured prompt engineering for students.
- 3) Incorporate Metacognitive Prompt Frameworks: Course designers can incorporate explicit metacognitive prompt frameworks in learning management systems (LMS), prompting the students to test their own knowledge, correct misconceptions, and schedule revision dates using conversational AI agents.
- 4) Institutional AI Equity and Access: HEIs should ensure that students have access to AI-agent technologies at the institution's level and in compliance with privacy laws, avoiding technological differences among students from different socio-economic backgrounds.
- 5) Future research is needed to perform longitudinal experimental studies in different academic fields (such as humanities and medical sciences) to monitor the effects of using

AI for learning long after the course is completed to measure how well students think and behave in their workplaces.

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