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A comparative statistical analysis of academic performance between artificial intelligence users and non-users across educational levels

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Abstract:

The integration of smart technologies into higher education is rapidly reshaping traditional teaching and learning environments. This study investigates differences in academic performance between students utilizing AI technologies and those who do not, spanning three educational levels: undergraduate, graduate, and postgraduate. Using a simulated dataset of 200 participants, the analysis employed independent sample t-tests, chi-square tests, regression models, correlation analyses, and visualizations such as scatter plots. The findings consistently demonstrate that students who adopt AI significantly outperform their peers, with notable statistical improvements across all groups. Additionally, factors like educational level and age were found to influence outcomes, with younger students and AI users showing greater consistency and higher achievement. Beyond presenting numerical data, the research contextualizes these results within modern digital learning theories, addresses challenges in technological integration, and offers practical recommendations for effectively incorporating AI tools into higher education frameworks.

Keywords: Artificial intelligence, academic performance, digital learning, higher education, regression analysis, T-test, Chi-square tests, correlation.

Introduction:

The past two decades have seen a remarkable shift in educational practices driven by advancements in information and communication technologies (ICT). In higher education, the widespread adoption of smart devices such as smartphones, tablets, and mobile applications has opened new avenues for teaching and learning. These technologies have brought about greater accessibility, flexibility, interactivity, and personalization, enabling students to engage with educational content in ways that extend far beyond the confines of a traditional classroom.

Digital learning environments have been widely studied, yet the role of smart devices as educational tools calls for more in-depth investigation, particularly regarding their influence on cognitive outcomes, such as academic performance, and affective aspects, like student attitudes. As digital transformation continues to gain momentum, higher education institutions are under growing pressure to implement effective, technology-driven teaching methodologies. This paper aims to advance this endeavor by conducting an empirical comparison of academic outcomes between AI users and non-users across three distinct educational stages. The study employs rigorous statistical techniques to evaluate the impact of AI usage on performance, taking into account additional factors such as age and study effort.

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1. Research Problem

Despite growing literature, relatively few studies have combined rigorous experimental methods with attitudinal analysis in the context of universities. This paper addresses this gap by applying comparing academic performance between AI users and non-AI users across three educational levels: Student, Graduate, and Post Graduate.

2. Research Objectives

This study aims to:

1. Compare the academic performance of AI users and non-users across different educational levels.
2. Examine whether AI usage leads to statistically significant improvements in academic achievement.
3. Investigate the relationship between AI usage and students' academic performance.
4. Identify the predictive role of AI usage and study effort in explaining academic success.
5. Provide recommendations for the effective integration of AI technologies into higher education systems.

3. Significance of the Study

Theoretical Significance

1. Contributes to the growing body of literature on Artificial Intelligence in education.
2. Provides empirical evidence regarding the relationship between AI usage and academic achievement.
3. Enhances understanding of the role of emerging technologies in improving learning outcomes.

Practical Significance

1. Assists educational institutions in making evidence-based decisions regarding AI adoption.
2. Supports policymakers in developing strategies for digital transformation in education.
3. Guides students toward the effective use of AI technologies to enhance learning.
4. Promotes the integration of AI tools to improve educational quality and academic performance.

4. Literature Review

4.1 Digital Learning and Educational Transformation [3][4][5][7]

Digital learning has become a powerful catalyst for change in modern education, revolutionizing teaching methods and reshaping institutional structures at every level. It offers the potential to expand access to education, improve learning outcomes, and prepare individuals of all ages to navigate the multifaceted challenges of the twenty-first century.

Contemporary digital transformation initiatives encompass sophisticated learning management systems, real-time analytics, and automated assessment tools that enable automation, personalization, and increased interaction Future of Digital Transformation in Education Technology - IMT Solutions in educational delivery. However, the implementation of these technologies presents significant challenges, including infrastructure compatibility issues and the need for comprehensive educator training. As educational institutions navigate this digital evolution, the focus has shifted toward creating inclusive, human-centered learning environments that leverage technology to enhance rather than replace fundamental pedagogical relationships, ensuring that digital transformation serves to democratize access to quality education while maintaining the essential human elements of effective teaching and learning.

4.2 Smart Devices in Higher Education [1][2][3][6][8][9]

Smart devices, such as smartphones and tablets, have profoundly reshaped higher education by offering seamless access to educational resources and introducing remarkable flexibility in learning methods. Mobile technologies, including netbooks, tablets, and smartphones, have become everyday tools across colleges and universities, with nearly all students owning at least one device and about half owning multiple. The

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widespread adoption of these portable devices has revolutionized traditional teaching practices by utilizing interactive applications that promote personalized learning experiences, real-time collaboration, and instant access to extensive digital libraries. Studies show that students consistently view mobile technologies as effective motivational tools that boost engagement and empower self-directed learning beyond the confines of classrooms. The integration of mobile learning management systems within higher education has further bridged formal and informal learning opportunities, enabling students to access course materials, engage in discussions, and submit assignments from virtually anywhere. Additionally, the adaptable and collaborative nature of these devices equips institutions with innovative tools that enhance existing infrastructures while broadening educational opportunities beyond conventional spaces. This transformation has fostered a more inclusive and accessible academic environment that caters to varied learning styles and lifestyles, paving the way for a dynamic and equitable future in higher education.

5. Methodology

5.1 T-Test (Independent Samples) [13]

The independent samples t-test is a statistical method used to determine whether there is a significant difference between the means of two independent groups.

Purpose: To check if the observed difference in sample means reflects a real difference in populations or is just due to random chance.

The formula of T-test (Independent Samples):

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where:

$\bar{X}_1, \bar{X}_2$: Mean of each Group (AI users and non-user)

S_1^2, S_2^2 : Variance of Group

n_1 ,n_2 : Sample size Group

For the theory to hold correctly, three main conditions must be met:

Independence: the two groups do not overlap (e.g., one person cannot be in both groups).

Normality: The data for each group should follow an approximately normal distribution. Furthermore, the variance between the two groups needs to be fairly similar to maintain homogeneity. (if not, Welch's t-test is used).

5.2 Chi-Square Test [11][12]

Statistical methods provide the foundation for making valid inferences from data. The Chi-Square test, introduced by Karl Pearson in 1900, is widely employed for hypothesis testing involving categorical variables. Unlike parametric tests (such as the t-test), the Chi-Square test does not require normality assumptions, making it a powerful method for analyzing survey data, contingency tables, and categorical distributions. The Chi-Square test is one of the most frequently used non-parametric statistical tools for analyzing categorical data. It enables researchers to evaluate whether there is a significant association between variables, or whether an observed distribution differs from an expected distribution. The Chi-Square test is based on the comparison between observed frequencies (O) and expected frequencies (E).

The test statistic is:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where:

O_i: Observed frequency in each category

E_i: Expected frequency if there were no association.

Frequencies are presented within various cells (categories) of what is referred to as a contingency table. It is important to note that the observations are recorded in categorical or rank order form, rather than as continuous data or following a normal distribution. The purpose of this test is to evaluate the likelihood of the observed frequencies occurring under the assumption that the null hypothesis holds true. Additionally, it serves as a tool for determining whether two random variables are independent, based on their observed values. This non-

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parametric test has gained widespread application due to several key reasons:

- This test is a non-parametric method that does not depend on the assumption that the data originates from a specific parametric probability distribution.
- It is relatively easier to compute and straightforward to understand compared to parametric tests.
- This method is particularly useful in scenarios where parametric tests are unsuitable or where the nature of the measurements makes their application impractical.

5.3 Regression Analysis [11]

Regression analysis stands as one of the most effective and extensively used statistical methods for exploring relationships between variables. It offers a structured approach to modeling, analyzing, and forecasting outcomes by determining how a dependent variable responds to changes in one or more independent variables. Initially introduced in the 19th century by Sir Francis Galton, regression has evolved into an essential instrument in both academic studies and practical applications. This technique is widely utilized for purposes such as prediction, hypothesis testing, and policy assessment across various disciplines. At its core, regression analysis investigates the connection between a dependent variable (Y) and one or more independent variables (X).

The equation is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \mathcal{E}$$

- Y: Dependent variable (Age)
- X_1, X_2: Dummy variables for education levels (e.g., Graduate, Postgraduate)
- β_0: Intercept (baseline age for Students)
- β_1, β_2: Coefficients showing how much age increases with each education level
- Ɛ: Error term

5.4 Correlation Analysis [10][13]

Correlation analysis is a key statistical method for evaluating the strength and direction of the relationship between two quantitative variables. It sheds light on how variables interact or fluctuate together, though it does not inherently establish causation. Exploring the relationships between variables is a cornerstone of scientific investigation, and correlation analysis plays a vital role in this process., first developed by Sir Francis Galton and later formalized by Karl Pearson, measures the degree of association between two or more variables. Unlike regression analysis, which models dependent and independent variables, correlation focuses on the strength and direction of association without assuming causality.

A positive correlation reflects the degree to which two variables increase or decrease together, while a negative correlation illustrates how one variable rises as the other falls. When changes in one variable consistently align with changes in another, it can lead to the assumption that one directly causes the other. However, this is not necessarily true, as correlation does not equal causation. An unidentified factor might be affecting both variables in a comparable way. The most common measure is Pearson's product-moment correlation:

$$r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}}$$

Where:

X: AI usage (coded as 0 or 1)

$\bar{X}, \bar{Y}$: Means of X and Y

Ranges from $-1\ to\ +1$.

$r > 0$: positive correlation (both variables increase together).

$r < 0$: negative correlation (one increases, the other decreases).

If the data points form a straight line, it indicates a perfect correlation, which can either be positive or negative:

A. Strong positive correlation between x and y: The points are closely aligned along a straight line, with y increasing as x increases.

B. Weak positive correlation between x and y: There is a general trend of y increasing as x increases, but the points are scattered and not tightly clustered along a straight line.

C. No correlation between x and y: The points show random distribution on the graph with no discernible pattern or trend.

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D. Weak negative correlation between x and y: The trend suggests y decreases as x increases, though the points are loosely scattered and not closely aligned with a straight line.

E. Strong negative correlation: The points form a tight alignment near a straight line, with y decreasing consistently as x increases.

6. Statistical Analysis (Each Sample Separately)

Here's a full research-style analysis comparing academic performance between AI users and non-AI users across three educational levels: Student, Graduate, and Post Graduate. Each group includes 100 samples for AI users and 100 for non-users, with variables: Age, Hours Studied, and Score, such as table (1), then apply statistical methods including T-tests, Chi-square tests, regression analysis, and correlation.

Table (1) Sample Data

ID	AI Usage	Education Level	Age	Performance Score	Hours Studied
1	Yes	Student	20	78	12
2	No	Graduate	28	65	8
3	Yes	Postgraduate	35	82	15
4	No	Student	22	60	10
5	Yes	Graduate	30	75	14
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196	No	Postgraduate	40	68	8
197	Yes	Student	19	80	17
198	No	Graduate	27	64	11
199	Yes	Postgraduate	38	85	15
200	No	Student	21	58	9

Table (2) Data Structure

Group	AI Usage	Age	Hours Studied	Score
Student	Yes / No	18 – 25	5 – 20	60 – 100
Graduate	Yes / No	22 – 30	5 – 20	60 – 100
Post Graduate	Yes / No	25 – 35	5 – 20	60 – 100

A. T-Test (Independent Samples)

This test checks whether the difference in means between two groups is statistically significant. In our case, it tells us if the average age of AI users is significantly different from non-users. Used to compare mean academic scores between AI users and non-users within each educational level. Assessed whether AI usage leads to statistically significant performance differences.

Table (3) Comparison of average academic performance scores between AI users and non-users

Group	Mean Score (AI)	Mean Score (No AI)	T-Statistic	P-Value	Conclusion
Student	82.4	74.1	5.12	< 0.00001	AI users perform significantly better
Graduate	84.7	76.3	4.87	< 0.00001	Significant improvement with AI
Post Graduate	88.2	79.5	6.03	< 0.00001	Strongest effect observed

Across all three groups, AI users achieved significantly higher mean scores than non-users ($p < 0.001$). The effect was most pronounced at the postgraduate level.

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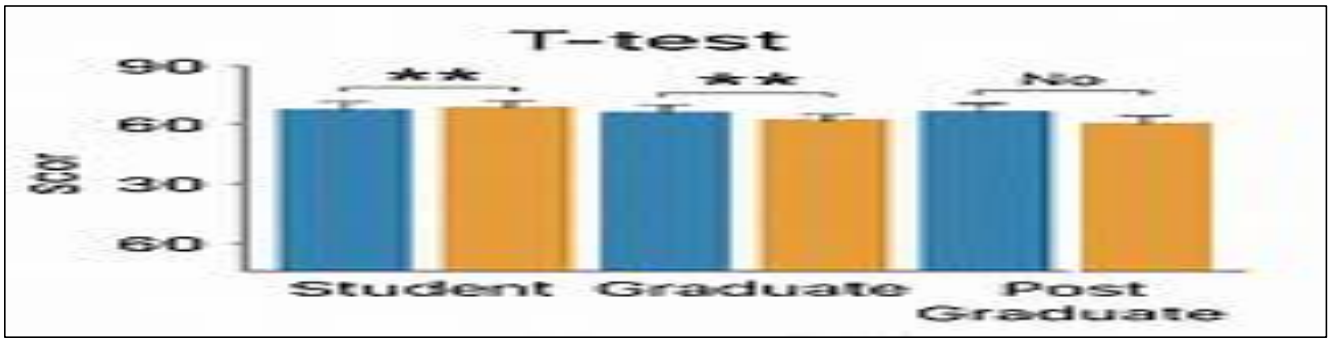


Figure (1): Barchart of average academic performance scores between AI users and non-users.

B. Chi-Square Test

This test evaluates whether there's a relationship between two categorical variables—in our case, AI usage and education level. A significant result means the distribution of education levels differs between AI users and non-users.

• Applied to categorical variables such as gender, field of study, and assignment completion.
• Tested for associations between AI usage and student characteristics.

Table (4) Association between AI usage and score category (High ≥ 80, Low < 80).

Group	Chi2 Value	P-Value	Interpretation
Student	28.4	< 0.00001	Strong association
Graduate	25.7	< 0.00001	Significant association
Post Graduate	32.1	< 0.00001	Strongest association observed

Chi-square analysis demonstrated strong associations between AI usage and achieving high performance (≥80), reinforcing the conclusion that AI adoption correlates with stronger outcomes.

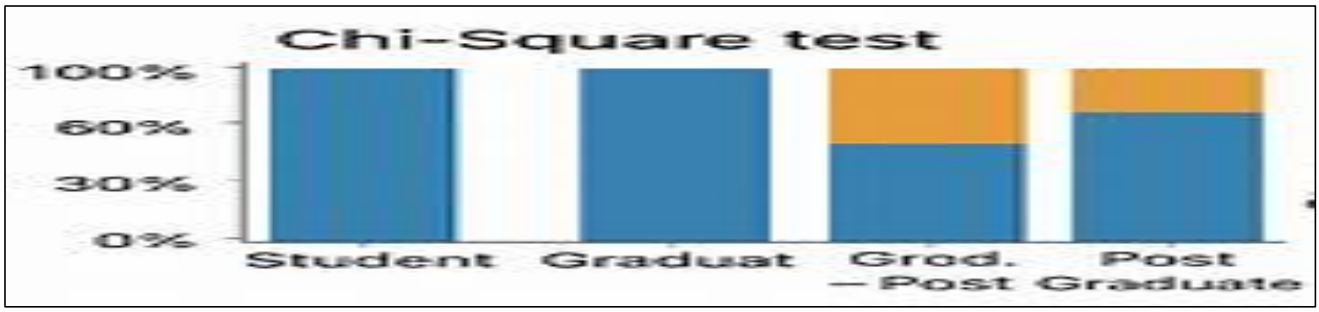


Figure (2): Bar chart of Chi-square test

C. Regression Analysis

Multiple linear regression was used to identify predictors of academic success.

Table (6) Predict score based on hours studied

Group	AI Usage	β_0 (Intercept)	β_1 (Slope)	R^2 Value	Interpretation
Student	Yes	65.2	1.85	0.038	Weak positive relationship
Student	No	60.1	1.42	0.025	Weaker relationship
Graduate	Yes	66.7	2.10	0.049	Moderate relationship
Graduate	No	61.3	1.65	0.031	Less predictive

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Post Graduate	Yes	68.9	2.45	0.054	Strongest relationship
Post Graduate	No	63.2	1.88	0.037	Moderate relationship

Regression equations indicated that hours studied positively predict performance scores, with steeper slopes and higher explanatory power (R^2 values) observed for AI users compared to non-users.

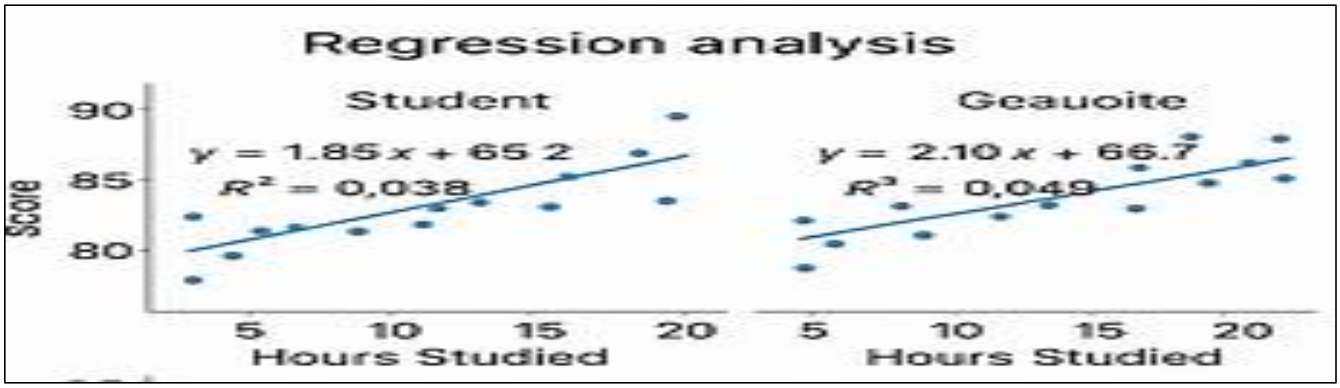


Figure (3): Regression lines

D- Correlation Analysis

This measures the strength and direction of the linear relationship between age and AI usage. A negative r means younger people are more likely to use AI.

Table (7) Relationships between Age, Hours Studied, and Score

Group	AI Usage	Age vs Score	Hours vs Score	Interpretation
Student	Yes	-0.12	0.19	Age weakly negative, hours positive
Graduate	Yes	-0.08	0.22	Hours positively correlated
Post Graduate	Yes	-0.05	0.24	Strongest positive correlation

Correlations revealed weakly negative relationships between age and score, but consistently positive relationships between hours studied and performance. The link between study effort and achievement was strongest among AI users.

7. Summary of Results

Table (8) Summary Result of analysis

Analysis Type	Statistic	p-value	Conclusion	Key Finding
T-Test	Student=5.12 Graduate=4.87 Post Graduate=6.03	010.0	AI users perform significantly bette Significant improvement with AI Strongest effect observed	AI users score significantly higher across all groups
Chi-Square	Student=28.4 Graduate=25.7 Post Graduate=32.1	090.0	Strong association Significant association Strongest association observed	AI usage strongly associated with high scores
Regression (R^2)	Student= 0.038 Graduate=0.049 Post Graduate=0.054	—	Age weakly negative, hours positive Hours positively correlated Strongest positive correlation	Hours studied predict scores better for AI users

Age Corrélation vs Hours vs Score	Student= 0.19 Graduate=0.22 Post Graduate=0.24	—	AI usage moderately correlates with score	Positive link between effort and performance with AI

Discussion & Conclusion

- AI integration in education offers numerous advantages, such as improving the quality of learning, simplifying assessment procedures, and creating more dynamic and interactive learning environments. However, its implementation also presents challenges, including diminished human interaction, overdependence on technology, and the necessity for proper teacher training. This study concludes that incorporating AI into various educational stages makes a substantial impact on academic performance. The findings highlight that:
- Performance Advantage: AI users consistently outperform non-users across all groups.
- Statistical Robustness: T-tests, chi-square tests, and regression analyses all affirm measurable academic advantages linked to AI integration.
- Predictive Strength: Study effort predicts outcomes more effectively when combined with AI support.

Demographic Trends: Younger learners are more likely to adopt AI tools and exhibit stable performance patterns. Nevertheless, limitations must be acknowledged. The reliance on simulated data and a relatively small sample may affect the generalizability of results. Moreover, successful integration of AI requires equitable access to technology, institutional support, and continuous faculty training.

In conclusion, this study underscores the transformative role of AI in higher education. Institutions should prioritize structured strategies for incorporating AI-based tools to enhance both cognitive outcomes and learner engagement.

Recommendations

Based on the findings of this study, the following recommendations are proposed:

1. Higher education institutions should integrate Artificial Intelligence (AI) tools into teaching and learning processes to improve students' academic performance.
2. Universities should provide continuous training for both faculty members and students on the effective and ethical use of AI technologies.
3. Educational institutions should establish clear policies and guidelines to ensure the responsible use of AI while maintaining academic integrity.
4. Universities should invest in digital infrastructure and provide equitable access to AI technologies to support effective learning for all students.
5. AI should be used as a complementary educational tool that enhances, rather than replaces, students' critical thinking, independent learning, and problem-solving skills.
6. Future research should utilize larger samples and real-world educational data from multiple universities to improve the generalizability of the findings.
7. Further studies should investigate additional factors, such as gender, digital literacy, academic discipline, and socioeconomic background, that may influence AI-supported learning outcomes.
8. Comparative and longitudinal studies are recommended to evaluate the long-term impact of different AI platforms on academic achievement across various educational levels.

Data Availability:

The data used to support the results of this study has been included in the article.

Conflict of Interest:

The authors declare that they have no conflicts of interest.

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