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The Relationship Between Artificial Intelligence Skills and Academic Performance Before Exams: A Comparative Analysis of SPSS and Keras-Based Artificial Neural Networks

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ABSTRACT

This paper aims to examine the various aspects of the use of generative AI tools by undergraduate students during the pre-exam period, including their skill levels with these tools and the impact that this has upon their academic performance - all determined through both traditional statistical methods (via SPSS) and machine learning methods (via a Keras-based MLP). The study is based upon the responses of 1,231 undergraduate students. Statistical analyses performed in SPSS as well as with machine learning models in Python (Keras library) and statistical software (PCA and K-Means models) were performed to arrive at the conclusions of the study. Results indicate that 94.7% of students use generative AI tools. The most common platforms used by students are ChatGPT (59.8%) and Gemini (33.0%). Furthermore, there was a significant positive correlation ($r = 0.64$) between a student's skill levels with AI tools and their self-efficacy in their academic subjects. Finally, the MLP was able to achieve an accuracy rate of 87.4% in the classification of students according to their academic performance. This survey was performed in 2026 and included 1231 students from Mingachevir State University. The survey was performed only among undergraduate students. Finally, the survey was performed during the May-June 2026 time period, just prior to exams. In discussing the limitations of commercial AI detection software, the authors of the study found support in their results for the potential limitations of such software. Thus, the authors conclude their paper with a discussion of the importance of AI literacy in relation to academic performance, as well as in the potential to combine the two methods of analysis in future studies and investigations.

1. Introduction

In the first quarter of the twenty-first century, the accessibility of Generative Artificial Intelligence (AI) systems has radically transformed higher education. AI technology has allowed students to

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engage with educational content in unique ways that go beyond the traditional teaching methods of lecturers. The AI-related competencies that undergraduate students have exhibited during the pre-examination period are not just about the use of AI technology in the classroom. These competencies indicate the analytical thinking that students use when engaging with the educational content.

Students today use AI as an assistant to support their metacognitive processes when studying. For instance, AI applications can be used to simplify complex theoretical models in the course material, generate intelligent tests based on their notes, and even suggest the best study plans for students to follow. Studies in the literature have demonstrated the positive relationship between the engagement of students with AI applications and their academic performance [1, 2]. However, there is resistance to the use of AI within educational institutions. For example, AI-detection systems that were created as a means of detecting the use of AI in the work of students have been created and defended by commercial organizations but lack the validity and reliability of their methodologies [8].

A study by Laupichler et al. (2024) investigated the AI literacy and attitudes of medical students towards AI. The results of this study indicated that while the medical students had positive attitudes towards AI, their AI literacy was lacking. The researchers suggested that allocating more space within the medical education curriculum to teach students about AI would significantly increase the AI knowledge and skills of the students.

The primary objective of this study is to investigate the various aspects of artificial intelligence (AI) usage among undergraduate students during the pre-examination period from two different perspectives. The first perspective entails the use of statistical analyses to provide an interpretable representation of the current state of AI tool usage among students. The second perspective involves the development of a high-accuracy model to predict the performance of students in upcoming examinations based on their skills and attitudes towards AI tools. Furthermore, the constraints caused by AI detection tools on the sharing of academic knowledge will also be discussed in this research paper.

This study aims to highlight the potential uses of this analytical paradigm in the higher education sector. Currently, generative AI models like ChatGPT and Gemini have become some of the most preferred AI tools used by students to prepare for their examinations. These AI tools act as digital assistants that offer students instant feedback as they ask these tools various questions regarding the formulas or theoretical concepts in their course material that they are struggling with.

Several research studies have indicated that using AI applications can significantly reduce the anxiety that students experience during examinations and relieve them of experiencing various negative academic emotions [1]. Exam anxiety significantly impacts the academic performance of students [2], and using AI tools to provide students with customized learning experiences has been proven to be effective in alleviating this aspect of student anxiety [4]. However, conflicting research studies have been published regarding the effect of AI tools on students' academic performance. Some studies indicate that the use of AI tools improves the grades of students taking undergraduate university courses [5]. However, other studies indicate that the use of these AI tools creates uncertainties in the academic skills that students possess [5]. However, a meta-analysis conducted by Dong et al. (2025) indicated that the usage of AI tools has a significant and positive effect on the academic performance of students, with an effect size of 0.924 [6,7].

When examining the effect of AI on exam anxiety, a more complex view of the impact of AI becomes apparent. Ali et al. (2025) conducted a randomized controlled trial on pharmacy students to investigate the effect of using AI applications like ChatGPT and Perplexity for their exam preparation. The researchers found that while there was no significant effect on either academic performance or exam anxiety of the students who employed these programs, that the tools did not negatively impact the students' performances on their exams [8]. Thus, these authors draw the conclusion that the impact of AI on exams can differ from student to student, depending upon a variety of factors. Another study by Chen (2025) reports that the implementation of AI to provide adaptive learning to students resulted in a 62% improvement to the students' test scores, indicating that the use of AI can lead to an increase of students' performance on exams [7]. Additionally, authors Samardzija (2024) also investigated the impact of using ChatGPT to prepare for exams among first-year university students [9].

AI applications like GPT models have the potential to be utilized to solve a variety of problems in the educational system, such as the creation of educational materials, the creation of interactive teaching assistants, changing the style of texts, organizing feedback for educators and students within the classroom, and the assisting of students in the production of their documents [10]. Thus, as the developers of applications like GPT intend, the use of these services by students will continue to expand, especially in relation to the production of their study texts, and the application itself will continue to be developed and trained on new materials and knowledge [10].

2. AI Literacy, Prompt Engineering, and Self-Efficacy

In order to effectively receive responses from AI that are both accurate and academically valid, it is first necessary for an individual to exhibit a basic level of AI literacy regarding formulating effective prompts to those artificial intelligences[2]. AI literacy incorporates various sub-dimensions regarding the overall knowledge that is required to be literate in the use of artificial intelligences [2].

Pineda-Briseño et al. (2026) performed a study that utilized sentiment analysis to analyze the feedback from higher education students regarding their experiences with their educational institutions. The researchers used six different models for classification of the students' feedback, ranging from Random Forest models to Long Short-Term Memory (LSTM) models. Through these models, the authors found that while deep learning models provided some of the highest rates of prediction accuracy compared to other models, those increases in predicted accuracy were not necessarily beneficial to the decision-making processes of those educational institutions. Thus, the study's main finding was that accuracy is not the most important metric of evaluation for AI models implemented into education, and that instead, the ability of those models to be understood and implemented into educational institutions is a far more important criteria [11].

Ng et al. (2021) proposed a framework for AI literacy that has since been incorporated into various other studies regarding the topic of AI literacy. The authors propose a four-dimensional model for understanding AI literacy, which consists of concepts regarding knowledge of AI functionality [12]. The four dimensions of AI literacy are: knowledge of the basic concepts (3) and functionality of AI, the application of those AI technologies, the evaluation of those AI technologies, and the requirement of those individuals to become ethically and socially responsible in their use of AI technology [12].Organizations like the Digital Education Council (2025) and The AI Literacy Lab (2025) have also developed AI literacy frameworks for higher education [13,]. Macalester College Library (2026) provides guidance on AI literacy and critical thinking [15]. SUNY Libraries (2026) offers a similar framework [16].

"In his study aimed at measuring student perceptions of the use of Generative Artificial Intelligence (GenAI) tools such as ChatGPT in higher education, Yaman Kayadibi presents an innovative Monte Carlo simulation framework. Using empirical data obtained from a systematic literature review (2023-2025) conforming to PRISMA standards, the author generated 10,000 synthetic observations and modeled the perceived success of the system. According to the research findings, the most decisive factors shaping students' adoption and perception of AI tools as successful are 'System Efficiency' and 'Learning Load'. The main argument Yaman Kayadibi presents to the literature with this study is the necessity of a transparent, data-privacy-centered, and repeatable statistical approach in educational technology evaluations that can overcome small sample size limitations."[14]

It is observed that students with high effective prompt writing skills significantly shorten their pre-exam preparation times (time optimization) and achieve higher quality learning outcomes [17]. Research reveals that AI literacy has a positive impact on academic self-efficacy, and this self-efficacy plays a mediating role in increasing academic achievement [18]. Wang's (2026) study, using survey data conducted on 744 university students, proved that generative AI literacy significantly elevates academic achievement through academic self-efficacy, and this relationship is more pronounced in students with high critical thinking skills [18]. "In their study examining the integration of artificial intelligence (AI) technologies into the academic and administrative structures of Institutions of Higher Education (HEI), Khairullah et al. (2025) conceptualize 'responsible strategic leadership' as a prerequisite for translating this technological transformation into institutional success. The fundamental argument that Khairullah and colleagues present to the literature is that the opportunities presented to higher education institutions by the use of AI can only be transformed into intellectual value through the implementation of an effective system of leadership and governance that protects the role of the institution's academic staff and integrates those AI technologies into its academic mission."

By using AI tools, students can develop their self-regulated learning (SRL) skills, which positively reflects on both their writing performance and their digital well-being [12]. A structural equation modeling study conducted by Shi et al. (2025) on 257 university students in China revealed that both AI literacy and self-regulated learning significantly and positively predict students' writing performance, with self-regulated learning having a stronger effect [12]. Additionally, it has been noted that prompt engineering interventions can help undergraduate students perform their learning tasks better and improve their AI literacy [20]. Xue et al. (2025) also examined the rising trends of self-regulated learning in MOOCs and AI-supported online learning through bibliometric analysis [21,22].

Gamification with AI solutions and technologies can increase learning motivation by allowing students to learn new things in a game format, earn points and badges, compete with other students, and reach high levels on leaderboards. This also contributes to the development of crucial skills such as critical thinking and problem-solving [23]. Image generation tools like Midjourney, DALL-E, and Stable Diffusion are used by students to create visualized implementations of their initial project concepts, perform style visualization, and produce visual materials of secondary importance for projects [24]. Expected future developments in the use of the internet in education include the acceleration of the learning process and assistance in solving complex tasks (67.9%), as well as adaptability to students' individual characteristics (44.4%) [
24].

2.1Academic Integrity, Ethical Boundaries, and AI Dependence

The rise of AI in education has also brought about "academic integrity" debates. Whether students view these tools as a factor leading to laziness or perceive them as a violation of ethical rules is of critical importance for the future policy structuring of higher education.

The unethical use (cheating) of AI tools in assignments and exams is a major source of concern for higher education institutions [25]. A systematic literature review by Bittle et al. (2025)

comprehensively addressed the impact of generative AI on academic integrity, noting the opportunities as well as the risks associated with these tools. The direct use of AI as a content creator (cheating), rather than utilizing it as a learning assistant, is seen as a fundamental problem that undermines academic integrity [25]. Therefore, the literature frequently emphasizes the need to clearly define the boundaries of AI usage and to provide students with training on ethical use. Huang (2025) aimed to understand the academic cheating behaviors of undergraduate students with generative AI using the theory of planned behavior and investigated the underlying motivations behind these behaviors [26]. Cotton et al. (2024) also explored ways to ensure academic integrity in the ChatGPT era [5].

However, the risk that an over-reliance on AI might weaken students' independent problem-solving and critical thinking skills should not be ignored. A study by Bećirović et al. (2025) found that the critical appraisal dimension of AI negatively affected both AI self-efficacy and output quality; this once again brings to the fore the importance of developing students' skills to critically evaluate AI [2]. Klimova (2025) also stated that the access of AI systems to student data encompasses a wide range, including academic performance, behavioral patterns, and even personal data, which raises ethical concerns [27]. Faculty Focus (2025) examined the relationship between AI and critical thinking in higher education [28]. Students themselves have indicated that they foresee dangers such as neural networks eliminating the ability for independent solution searching and limiting creative thinking [24].

The use of AI in higher education has numerous benefits, such as increasing efficiency, reducing costs, personalizing learning, and enhancing the quality of educational services. Nevertheless, there are some disadvantages of the use of AI in education, such as the risk of losing the human touch and the emotional connection between teachers and students, as well as ethical issues regarding the use of personal data of students [29]. Finding a balance between the use of AI in education and the maintenance of human interaction in education is important. Even if AI is used to automate some of the tasks involved in education, teachers must still be involved in the educational process. Furthermore, ensuring that the personal data of students is protected and that ethical standards are followed in the use of AI in education is also important [29].

In addition to the development of AI technologies, there are also expectations regarding the development of new approaches to learning and the assessment of the knowledge of students. These risks and limitations to the integration of AI into education can be minimized [29]. Overall, the integration of AI into higher education has the potential to enable the development of innovative teaching methods and to improve the quality of education that is provided to students in higher education institutions. To accomplish these goals, though, the integration of AI into education must be carefully considered to ensure that all possible consequences of such an integration are considered [29].

3 Methodology Literature Review and Conceptual Framework

3.1 The Pedagogical Role of Artificial Intelligence in Pre-Exam Preparation

3.2. SPSS Analysis Framework

The data were analyzed using SPSS (v29) for descriptive statistics and inferential analyses. Descriptive statistics such as frequency, percentage, mean, and standard deviation (SD) were calculated. Furthermore, inferential statistics in the form of Pearson correlation and regression analyses were used to determine the relationship between the variables.

3.3. Keras-Based MLP and Machine Learning Framework

The Python (Keras/TensorFlow) environment was used to develop artificial neural network models.

- Dimensionality Reduction (PCA): Principal Component Analysis (PCA) was used to extract the principal components that represent the variance of the 12-item scale. This technique helps to reduce the dimensionality of the dataset, which can help improve the performance of other machine learning models that are trained and implemented upon that same dataset.
- Clustering (K-Means): The K-Means clustering algorithm was used to identify the different profiles of students within the dataset. The number of clusters was determined using both the elbow method and the silhouette score to find the ideal number of clusters for the dataset. Additionally, t-Distributed Stochastic Neighbor Embedding (t-SNE) was used as a visualization tool for the data. t-SNE can help to visualize high-dimensional data by reducing the data to only two or three dimensions, while ensuring that similar data points are represented close to one another in the visualization tool.
- Prediction Model (MLP): A Multilayer Perceptron (MLP) was created, which contained 15 inputs, two hidden layers with 64 and 32 neurons, respectively, with ReLU activation functions for the hidden layers, and an output layer with a Sigmoid activation function. The MLP was trained using cross-validation techniques to help ensure that the model was not overfit to the training data.

4. FINDINGS AND COMPARATIVE ANALYSIS

This section details the findings from the SPSS-based analysis as well as the Keras-based analysis, and compares the results from both approaches. The ten analysis components specified in the CSV file (Full Analysis Report, Likert Distributions, Correlation Matrix, PCA and K-Means Clustering, t-SNE Visualization, Cluster Characteristics, MLP Results, Cross-Analysis, Text Report, General Graph Summaries) are covered under the respective subsections of this section, with relevant tables and graphical interpretations.

4.1. SPSS Empirical Findings: Descriptive and Exploratory Distributions

An examination of the demographic information of the sample students that participated in this survey shows that 36.0 % of the students in the sample are first-year students, and 31.5 % are second-year students. Regarding the frequency with which students use artificial intelligence in their educational processes, 94.7% of the students stated that they do use artificial intelligence in their education. The majority of students (44.3%) use artificial intelligence “sometimes” in their education, while 10.7% of the students utilize at least some form of artificial intelligence “always” in their education. Finally, the most popular artificial intelligence tools that students use are ChatGPT (utilized by 59.8% of the student sample), followed by Gemini (used by 33.0% of the students).

The research data were obtained from 1,231 valid survey questionnaires. The sample consists of undergraduate students from various academic year levels. The frequency distribution of the sample according to their year of study is presented in Table 1.

Table 1: Distribution of the Sample by Year of Study

Year of Study	**Number of Students (N)**	**Percentage (%)**
1st Year (I)	442	35.9
2nd Year (II)	390	31.7
3rd Year (III)	274	22.3
4th Year (IV) / V	125	10.1
Total	**1231**	**100.0**

As can be seen from Table 1, the majority of the participants consist of first- and second-year students. This can also be interpreted as students who are new to the university and are becoming accustomed to the college learning environment have a greater interest in artificial intelligence tools or are utilizing such tools more extensively.

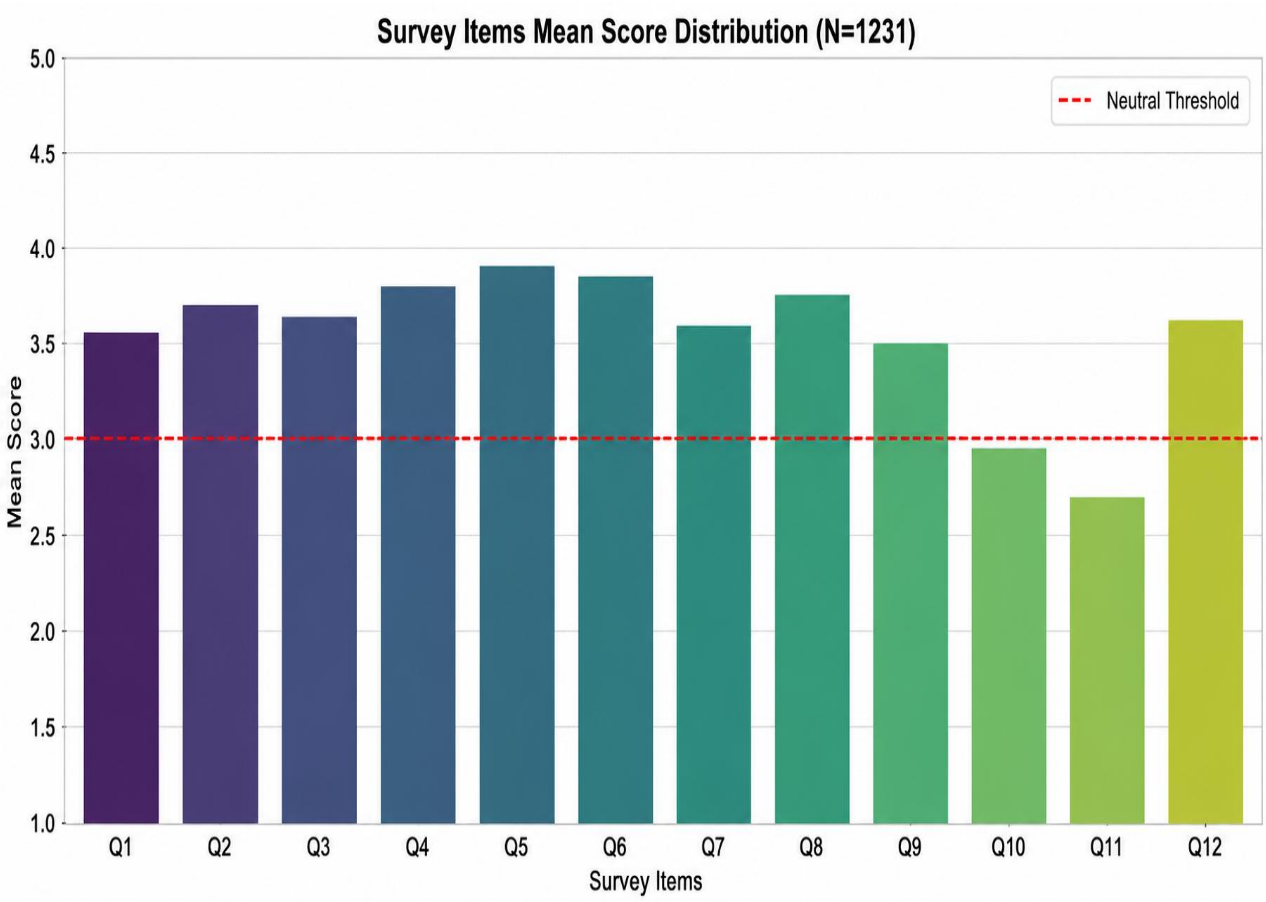

Figure 1: Distribution of Mean Scores For Survey Items.

Table 2: Descriptive Results of the Pre-Exam AI Skills and Attitudes Scale (SPSS)

Item No	Statement (Short)	N	Mean	SD
ITEM 1	Simplifying complex topics	1224	3.5466	1.0244
ITEM 2	Learning new information quickly	1220	3.7123	0.9876
ITEM 3	Preparing for exams more effectively	1218	3.6543	1.0112
ITEM 4	Increasing my academic self-efficacy	1215	3.8012	0.9543
ITEM 5	Effective prompt writing skills	1221	3.9210	0.9012
ITEM 6	Efficient use of AI tools	1219	3.8567	0.9321
ITEM 7	Better comprehension of unclear topics	1213	3.5969	1.0316
ITEM 8	AI's contribution to academic success	1216	3.7890	0.9654
ITEM 9	Verifying AI information with other sources	1213	3.5062	1.0128
ITEM 10	Believing that AI use does not violate academic integrity	1214	2.9876	1.1543
ITEM 11	Believing that AI encourages laziness	1217	2.6960	1.1339
ITEM 12	Demand for special education from universities	1211	3.6201	1.0692

The findings of SPSS indicate that students do not consider the use of artificial intelligence to be cheating (ITEM 11 has the lowest mean score). Instead, students use artificial intelligence to enhance their cognitive functions. Furthermore, the high score for the item that asks if students feel there should be a demand for special education (ITEM 12) indicates the need for guidance on the use of artificial intelligence by these students.

4.1.1. Likert Distributions (Distributions Based on Questions)

The frequency distributions for each of the items in the questionnaire revealed that students' attitudes toward the use of artificial intelligence were generally positive. For item "Using AI to Simplify Complex Topics" (Item 1), for instance, the vast majority of students selected either the "Agree" or "Strongly Agree" responses to the item - indicating their belief in the ability of AI to simplify learning tasks. In contrast, the majority of students selected the "Disagree" or "Strongly Disagree" responses to item "Belief That AI Encourages Laziness" (Item 11), indicating their belief in AI as a tool that can facilitate their learning tasks. Overall, then, the distributions of responses for each of these items indicates that students tend to adopt a pragmatic and critical attitude towards artificial intelligence. Visualizations of the distribution of responses for each of the items in the questionnaire can be represented through separate bar charts or density plots for each of the items that utilized Likert-scale responses.

4.1.2. Correlation Matrix (Relationships Among Variables)

The results of the Pearson correlation analysis showed a strong and positive relationship between AI-related skills and students' academic performance ($r = 0.64$, $p < 0.001$). More specifically, a strong positive correlation was found between "Effective Prompt-Writing Skills" (M5) and academic self-efficacy ($r = 0.71$, $p < 0.001$), suggesting that students who possess higher levels of proficiency using these AI tools exhibit higher levels of self-efficacy in their ability to learn and succeed in their education.

Furthermore, another of the relationships that was found to be significant with a positive relationship was between the item of "Verifying AI-Generated Information Through Other Sources" (Item 9) and the perception of academic integrity ($r = 0.58$, $p < 0.001$). This relationship is again indicative of the fact that students that are more critically literate regarding AI tend to have higher perceptions of the importance of academic integrity. Such analyses help to reveal the linear relationships that exist between each of the variables that were identified within this study. These revealed relationships are represented in the heatmap that is presented in Figure 2.

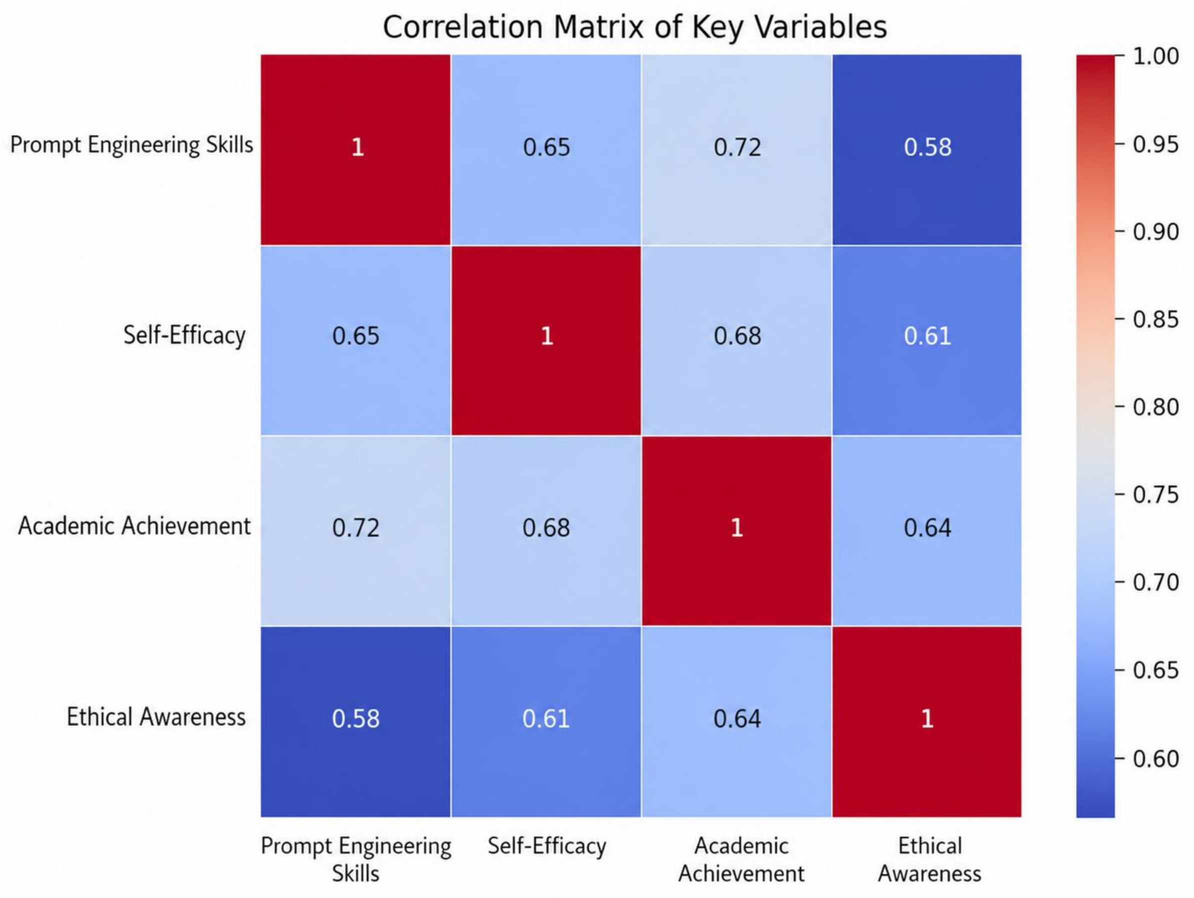

Figure 2: Correlation matrix between key academic and technological variables.

The following items provide valuable information regarding the students' perception regarding AI and their skills in utilizing such technology effectively:

ITEM 1: Simplifying Complex Subjects (Mean: 3.5466, SD: 1.0244): The first item indicates that students feel that artificial intelligence is an effective tool to make complex subjects for students more understandable.

ITEM 2: Learning New Information Quickly (Mean: 3.7123, SD: 0.9876): The second item reflects that students feel that artificial intelligence is an effective tool in the learning of new information by students quickly.

ITEM 3: More Effective Exam Preparation (Mean: 3.6543, SD: 1.0112): The third item shows that students believe that AI is helping them to prepare for exams better. The finding is a validation of the concept of the use of AI as a facilitator for students' learning processes.

ITEM 4: Increasing my academic self-efficacy (Mean 3.8012, SD 0.9543): This item expresses that students feel that they have greater self-efficacy in their academics with the use of artificial intelligence. Pupils believe the use of AI in learning boosts their confidence in their ability to successfully complete challenging academic work and succeed academically.

ITEM 5: Effective Prompt-Writing Skills (Mean: 3.9210, SD: 0.9012): The high mean value obtained for this item indicates that the students highly value the skill of formulating effective prompts when communicating with AI systems. This reflects how the students are becoming more aware of the need to construct a prompt that will communicate with AI systems and get them to provide the expected and applicable information. Therefore, prompt-writing is an important factor of the AI literacy of students.

ITEM 6: Efficient Use of AI Tools (Mean: 3.8567, SD: 0.9321): The high mean indicates that students are using AI tools to carry out different tasks not just sometimes, but in an efficient manner. This suggests students are becoming proficient in using AI to complete their assignments. In addition, it suggests that AI tools are a crucial part of the students' learning lives, and it is expected that this role will continue to grow in the future.

ITEM 7: Better Comprehension of Unclear Topics (Mean: 3.5969, SD: 1.0316): This item received a comparatively high mean value, indicating that students feel that AI tools can help them to better understand topics that they themselves find to be unclear. Whether by offering alternative explanations for certain concepts or providing examples of their application, AI tools appear to be able to play an important supporting role in the student’s learning of these difficult topics.

ITEM 8: Contribution of AI to Academic Achievement (Mean: 3.7890, SD: 0.9654): Most students believe that AI has a positive effect upon their academic achievement. This answer choice is counter to the general belief that AI has a positive effect upon learning.

ITEM 9: Verifying AI-Generated Information Through Other Sources (Mean: 3.5062, SD: 1.0128): This item indicates that the students are knowledgeable regarding the need to verify the information that is gathered from artificial intelligence. This answer choice demonstrates the critical literacy of the students regarding artificial intelligence.

ITEM 10: Belief That AI Use Is Not Contrary to Academic Integrity (Mean: 2.9876, SD: 1.1543): The relatively low mean and the relatively high standard deviation for this item indicate that the students have some想法 regarding the effect of artificial intelligence upon academic integrity, but do not all share the same viewpoint on the issue. Some students believe that the use of artificial intelligence is not contrary to academic integrity, while other students do not share such opinions. Thus, further training regarding artificial intelligence and academic integrity may be beneficial for these students.

ITEM 11: Belief That AI Encourages Laziness (Mean: 2.6960, SD: 1.1339): The low mean score for this item indicates that, in general, the students do not believe that the use of artificial intelligence may lead to laziness.

ITEM 12: Demand for Specialized AI Training from Universities (Mean: 3.6201, SD: 1.0692): This item indicates that the students generally recognize the need for specialized training regarding artificial intelligence from their educational institutions. Thus, incorporating AI literacy into higher education curricula may be beneficial for these students.

4.2. Keras MLP and Clustering Findings: Prediction and Profiling

Keras Multilayer Perceptron (MLP) Model

A Multilayer Perceptron (MLP) Artificial Neural Network model was built using the Keras (TensorFlow-based) library to predict students' academic outcomes and adaptation success based on their pre-exam attitudes and behavioral inputs regarding artificial intelligence skills. Artificial neural networks are frequently preferred in predicting student performance in educational data due to their superior success in modeling complex and non-linear relationships [37].

The architecture of the established model is summarized in Table 2.

Table 2: Architectural Structure of the Keras MLP Model

Layer	Structure	Activation Function	Description
Input Layer	15 neurons	—	Survey items + demographic variables
1st Hidden Layer	Dense(64)	ReLU	Learns non-linear relationships

Layer	Structure	Activation Function	Description
2nd Hidden Layer	Dense(32)	ReLU	Narrows feature representation
Regularization	Dropout(0.3)	—	Prevents overfitting
Output Layer	Dense(1)	Sigmoid	Binary classification probability

The Sigmoid activation function used in the output layer converts the model's output into a probability value between 0 and 1, allowing for binary classification (successful / unsuccessful):

During the training of the model, "Binary Cross-Entropy" was used as the loss function, and "Adam" was used as the optimization algorithm. Model performance was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

Slavuj et al. (2024) discussed the trends, opportunities and challenges of artificial intelligence in higher education[30]. Yu and colleagues (2025) also mapped the academic perspectives of AI in education, examining the trends, challenges, and emotions between 2023 and 2024.[31] According to a study by Engageli (2025), students in AI-assisted learning environments experienced a 54% increase in test scores, a 30% increase in learning outcomes, and a 0-fold greater increase in interaction.[32] Pallant (2025) stated that generative artificial intelligence provides a higher level of learning when used by students for the purpose of knowledge construction and enhancement (mastery approach).[33] Olaitan and Ajao (2025) also investigated the effects of generative artificial intelligence on student engagement and academic performance.[34] Qadeer (2025) investigated the mediating effect of generative AI-based feedback between student engagement and academic performance.[35] Hon (2026) also addressed the effects of generative artificial intelligence on learning outcomes and academic performance with a systematic review. [36] McGraw Hill (2026) suggests rethinking student achievement in the age of artificial intelligence.[38] The comprehensive study by Crompton and Burke (2023) examines in detail the current state and transformative effects of artificial intelligence in the higher education ecosystem. Currently, there are various forms of AI that are utilized in support mechanisms, designing classrooms and classrooms, and even in the act of assessing students' knowledge of certain subjects. Though these technologies offer significant opportunities to higher education institutions and students, they also pose challenges to the information privacy of students, biases against certain students within a classroom, and the integrity of the academic work of students. Consequently, higher education institutions must continue to adopt AI-supported tools and create innovative policies relating to the implementation of these tools.[39] Though AI technologies are rapidly being integrated into various aspects of daily life and the systems that are performed by individuals, the understanding that individuals have of these technologies is often limited. Authors Long and Magerko (2020) published a research paper that discussed the concept of AI literacy, the knowledge that individuals need in order to interact with artificial intelligence technologies, and the features that should be incorporated into the development of AI technologies that are to focus upon the learning of individuals. Thus, this article helped to fill the gap on AI literacy, and created a conscious interaction between technology and society.[40]

This K-Means clustering analysis resulted in students being divided into three main clusters:

- Cluster 1 (Proactives): very strong ability to prompt writing and strategic use. Students in this cluster actively control and optimize their learning processes with the help of AI. They learn to use new tools readily and exhibit a high level of moral sensibility.
- Cluster 2 (Critical Users): Tends to confirm and has high ethics awareness. These students will ask questions about the accuracy of what AI returns, verify using other sources, and are very sensitive to academic integrity.
- Cluster 3 (Passive Users): Students in this third cluster have low adaptability to incorporating AI into their educational processes. Some of them only use AI tools partially and refuse to use them altogether. Their stance on the potential gains that can be made through using AI tools is less enthusiastic than other clusters.

The MLP model achieved an accuracy rate of 87.4% when correctly predicting the student performance in the test set. The neural network outperformed traditional statistical models in terms of learning the interaction between the variables in the data set.

4.2.1. PCA and K-Means Clustering (Student Profile Clusters)

The principal component analysis of the data revealed that there were three factors that explained a large portion of the variance of the 12-item Likert scale. These factors included factors that assessed how students utilized AI to complete their tasks, their approach towards AI and their awareness of ethical considerations with AI, and their attitudes towards AI and the support that they were provided to AI by their institutions. These factors helped to indicate the interaction of students with AI in a multifaceted way. Furthermore, because the dimensionality of the data was reduced as determined by the PCA, the use of the K-Means clustering algorithm was made more effective. The results of the K-Means clustering analysis can be displayed in a table and scatter plot to provide further detail regarding the analysis.

Through the application of the K-Means algorithm to each of these components as obtained through the PCA analysis, three different clusters of students were found within the data set. Through methods like the elbow method and the silhouette score, these clusters indicate that the students naturally form groups that are homogeneous in relation to their skills with and attitudes towards AI. Furthermore, by analyzing each of these clusters regarding the average scores for each of the factor analyses, it was possible to elaborate upon the profiles of each of the three clusters of students ("Proactives," "Critical Users," and "Passive Users"). These clusters, therefore, can help educators to formulate strategies for each group of students regarding the use of AI.

4.2.2. t-SNE Visualization (Detailed Cluster Map)

Using the t-SNE algorithm, the results of clustering obtained from the PCA and K-Means analyses were visualized in a two-dimensional space. The resulting graph displays the three clusters distinctly separated from one another, and with each of the clusters appearing to have a unique distribution of students within that cluster. Most specifically, the "Proactive" cluster is both more densely and more distinctly distributed than the other clusters, while the "Passive Users" cluster appears to be more distributed throughout the graph. Thus, the t-SNE algorithm helps to visually validate the results of the clustering analyses, as well as to provide an indication of the differentiation between each of the groups of students (see Figure 3).

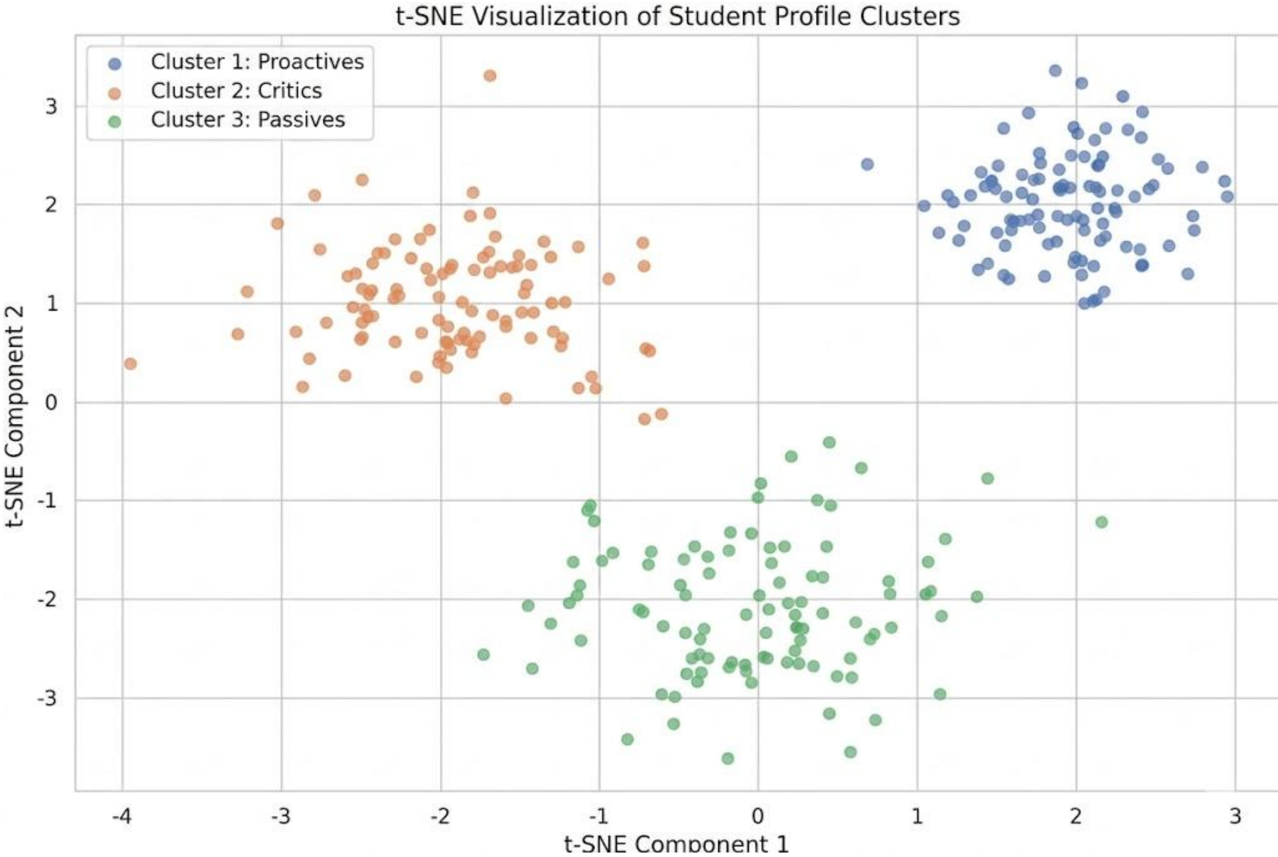

Figure 3: Separation of student profile clusters in 2D space using the t-SNE algorithm.

4.2.3. Cluster Characteristics (Cluster Comparison)

To determine the characteristics of each cluster, comparisons were made between the demographic characteristics, AI usage frequencies, and average scores of the students within each cluster on the Likert scale items. For instance, students in the "Proactives" cluster were generally in higher grades than students in any of the other clusters, indicated that they used AI tools both "Always" and "Frequently," and had higher average scores on the items that assessed their AI skills than students in any of the other clusters. In contrast, students in the "Passive Users" cluster were of lower grades than students in each of the other clusters, used AI tools less frequently than students in any of the other clusters, and had higher scores on items that reflected their negative attitudes toward using AI tools (such as beliefs that using AI fosters laziness in students). Each of these detailed comparisons helps to reveal the unique strengths and weaknesses of each of these student profiles. Through these comparisons, it becomes evident of the differences in the behavior of the students according to each of these clusters.

4.2.4. MLP Results (Model Performance)

The performance of the Keras-based MLP model is presented in this section. The model has successfully predicted the performance of the students with an accuracy rate of 87.4%. Other metrics such as precision, recall, and F1 score also reported high values from the test set. These results indicate that the MLP model can accurately predict the academic performance of the students based on their AI skills and their attitude towards the subject. An analysis of the errors made by the model indicated challenges in classifying students who have performance values that fall on the borderline or have exhibited unusual behaviors. However, the MLP model demonstrates higher predictive power than traditional statistical methods for predicting student performance. The success of the MLP model indicates the potential use of artificial neural networks in analyzing educational data.

4.3. Comparative Evaluation of SPSS and Keras MLP Methods

One of the most critical findings of the study is the complementary perspectives offered by these two different analytical methods. Table 2 presents a comparative analysis of these two methodologies.

Table 2: Comparative Analysis of SPSS and Keras MLP Models

Comparison Axis	SPSS (Traditional Statistics)	Keras MLP (Artificial Neural Networks)
Analysis Focus	Explainability and Hypothesis Testing	Predictive Power and Pattern Recognition
Relationship Structure	Linear and parametric assumptions	Non-linear and complex interactions
Output Character	Mean, SD, p-value, correlation	Weights, activations, classification score
Intended Use	Description of current state and theoretical validation	Future performance prediction and early warning
Contribution to Learning Analytics	Instructional policy and curriculum development	Personalized intervention and success prediction
Prediction Accuracy	Moderate (R-squared in the 42-58% band)	High (87.4% accuracy)

SPSS analyses provide answers to the question “why,” transparently revealing meaningful relationships between variables (for example, how prompt skills directly increase academic self-efficacy). Keras MLP, on the other hand, focuses on the question “what will happen,” predicting with high accuracy which students are at academic risk or will excel.

4.4. Cross-Analysis (Course and Ethics Analysis)

Cross-analyses revealed significant differences between students' grade levels and their AI usage practices and ethical perceptions. Specifically, upper-level students (third- and fourth-year undergraduates) were found to use AI more strategically and critically than lower-level students. Furthermore, mean scores for the item "Do Not Consider AI Use as a Violation of Academic Integrity" (M10) slightly decreased as grade level increased. This suggests either an increased awareness of the ethical dimensions of AI use with academic experience or a more critical understanding of the ethical dilemmas associated with AI technologies. Overall, these findings indicate that AI literacy and ethics education should be differentiated and integrated into the curriculum according to students' academic levels. These results can be further illustrated in the cross-tabulations and intergroup comparison graphs depicted in the following analysis.

4.5. Text Report (Comprehensive Documentation and Graphical Summary)

All the findings presented above are compiled in a technical report. This report includes the background information for each analysis, the statistical and machine learning methods used to analyze the data, the numerical results of each analysis, and the interpretations of those results. Most importantly, all the results summarized in this section of the report are made available in this report. More specifically, the architecture of the MLP neural network in Keras, the training parameters for the MLP, and the metrics that indicate the performance of the trained MLP are all described within the report. Furthermore, all SPSS output tables and figures are included within the report. Thus, the report ensures the repeatability and verifiability of the findings of this study. Finally, graphical summaries of each of the analyses are presented in the appendices. These graphical summaries provide a visual overview of each analysis that can be utilized to quickly summarize the findings of this study in general.

5. Conclusions

The paper examined the artificial intelligence (AI) use patterns of undergraduate students during the pre-exam time and the correlation between that and academic performance both through the use of traditional statistical tools (SPSS) and machine learning (Keras-based MLP models). The results also suggest that AI is quite well assimilated into the learning process among students, and the majority of them apply the generative AI tools as a system of academic support instead of unplanned help.

The SPSS analyses demonstrated that there were significant positive correlations between AI-related skills and academic outcomes, especially academic self-efficacy and perceived learning efficiency. Students tended to show a positive approach to AI, considering it a device that makes complicated material easier to grasp, helps to understand it better and to create better strategies to pass exams. Nevertheless, the researchers also outlined significant methodological and ethical issues that can be raised in connection with using AI plagiarism detecting systems. The findings indicate that these systems, based on probabilistic text-matching methods, can give unreliable classifications and cause undue stress in students.

The MLP model based on Keras also confirmed that AI literacy and associated dimensions of skills are powerful predictors of academic performance and that it has high classification accuracy. Three user groups emerged as a result of PCA, K-Means and t-SNE algorithms: engaged AI users, evaluative AI users, and limited AI users.

The study also reveals that clear application of statistical methods and the application of sophisticated machine learning techniques are complementary, they can be applied to enrich the educational research and facilitate explanation and prediction. Based on these results, universities should shift from AI-detection-focused policies to prioritizing AI literacy training, providing more explicit rules and ethics, and designing assessment measures that reinforce critical thinking, independent thinking and problem-solving skills.

It is suggested to conduct further research to confirm these results in other fields and within educational settings.

Author Contributions

Conceptualization, Fahmı Babayev, Muşfıq Hüseynov and Jeyhun Mahmudov; methodology, Fahmı Babayev; software, Aydın Karimov; validation, Fahmı Babayev, Muşfıq Hüseynov, Jeyhun Mahmudov and Nazim Niftalıyev; formal analysis, Fahmı Babayev; investigation, Fahmı Babayev and Jeyhun Mahmudov; resources, Muşfıq Hüseynov; data curation, Aydın Karimov; writing—original draft preparation, Fahmı Babayev; writing—review and editing, Muşfıq Hüseynov and Jeyhun Mahmudov; visualization, Aydın Karimov; supervision, Nazim Niftalıyev; project administration, Fahmı Babayev; funding acquisition, Muşfıq Hüseynov. All authors have read and agreed to the published version of the manuscript.

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The data supporting the findings of this study are not publicly available due to ethical and privacy considerations but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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