

RESEARCH ARTICLE

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An Empirical Study of Student Usage Patterns, Dependency and Ethical Perceptions

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Abstract: This study empirically examines the prevalence, purposes, and ethical perceptions of Artificial Intelligence (AI) tool utilization among higher education students. **Design/Methodology:** A quantitative, cross-sectional descriptive survey was administered to 120 students spanning undergraduate and postgraduate levels across multiple academic disciplines. The collected data was analyzed using descriptive statistics and three Chi-Square Tests of Independence at a significance level of $\alpha = 0.05$. **Findings:** The study found that ChatGPT (80.0%), Google Gemini (68.3%), and Claude (56.7%) are the dominant platforms. A significant relationship was confirmed between a student's field of study and their dependency level ($\chi^2 = 18.42, p = 0.0306$), between usage frequency and perception of reduced creativity ($\chi^2 = 21.55, p = 0.0003$), and between daily time spent and verification behavior ($\chi^2 = 13.21, p = 0.0398$). A critical verification gap was identified: only 27.5% of students consistently verify AI-generated content, while 60.8% have submitted AI-generated text with minimal editing.

Keywords: Artificial Intelligence, AI literacy, student dependency, ChatGPT, academic integrity, verification gap, higher education

1. Introduction

The use of Artificial Intelligence (AI) tools in education has increased significantly in recent years, particularly with the emergence of generative AI platforms such as ChatGPT, Google Gemini, Claude, and Microsoft Copilot. These tools can assist students with a wide range of academic tasks, including writing assignments, preparing for examinations, conducting research, generating code, and understanding complex concepts. Their ease of access and ability to provide instant responses have made them increasingly popular among students across different disciplines.

While AI tools offer several benefits, including improved productivity and faster access to information, their growing use has also raised concerns among educators and researchers. Issues such as overreliance on AI, reduced critical thinking, academic integrity, and the accuracy of AI-generated information have become important topics of discussion in higher education. Previous studies have suggested that students may not always verify AI-generated content before using it for academic purposes, increasing the risk of misinformation and inappropriate academic practices [3], [5], [10].

Existing research has explored the educational applications of AI and students' attitudes toward these technologies. However, there remains limited empirical evidence regarding how students from different academic disciplines use AI tools, the extent to which they depend on them, and how they perceive the ethical implications of AI-assisted learning, particularly within the Indian higher education context [4], [7]. Therefore, this study examines the prevalence of AI tool usage among higher education students and investigates patterns of dependency, verification behaviour, and ethical perceptions. Using survey responses collected from 120 students, the study employs descriptive statistics and Chi-Square Tests of Independence to analyse relationships between key variables related to AI adoption and academic behaviour.

1.1 Objectives of the Study

The primary intent of this research is to deconstruct the factors determining student engagement with automated writing systems and the resulting ethical quality-control behaviours. The explicit research objectives are:

1. To document the demographic characteristics and baseline

usage distributions of generative software among university students.

2. To determine the most popular generative platforms and map their primary use cases across academic tasks.
3. To evaluate the relationship between a student's chosen major and their self-perceived dependency on automated tools.
4. To analyze whether the frequency of software interaction shapes a user's awareness of potential critical thinking decline.
5. To measure the extent of student fact-checking habits and their general attitudes toward academic honesty.

1.2 Organization

The remaining parts of this manuscript are structured into seven distinct chapters. Section 2 contextualizes the study by examining prior international research on technology adoption, dependency loops, and academic integrity issues. Section 3 outlines the mathematical foundations and core operational assumptions behind non-parametric contingency tests. Section 4 clarifies the experimental methodology, explaining the cross-sectional survey setup, variable classifications, and Python-based analysis stack. Section 5 presents the descriptive results and interprets the inferential outcomes of the three Chi-Square tests. Section 6 offers practical institutional suggestions and identifies boundaries for future tracking, and Section 7 summarizes the core takeaways of the study.

2. Literature Review

The rapid growth of AI technologies has significantly transformed the educational environment. Tools such as ChatGPT, Google Gemini, and Claude have changed how students approach research, writing, coding, and exam preparation, creating both opportunities and challenges for academic institutions. Kasneci et al. (2023) [10] discussed the opportunities and risks of generative AI in education, highlighting support for personalized learning and accessibility while cautioning about overdependence and undermining critical thinking. Cotton et al. (2023) [5] found that students frequently use AI for brainstorming, summarizing, and preparing drafts, noting both productivity gains and risks of plagiarism. Dwivedi et al. (2023) [7] identified that adoption of AI tools was noticeably higher among technical and quantitative students compared to those

Baidoo-Anu and Ansah (2023) [3] found that students widely use AI for essay writing, coding assistance, and language improvement. Lo (2023) [11] revealed that a significant number of students had submitted AI-generated text with minimal modifications, pointing to a growing “verification gap.” Chan and Hu (2023) [4] observed that AI was commonly used for note-making, exam preparation, and simplifying complex concepts. Dahri et al. (2024) [6] highlighted that students in Pakistan and Malaysia preferred AI tools for their ease of use and ability to improve academic outcomes. Although several studies have explored AI adoption and ethical concerns, limited research has focused on these dynamics within an Indian regional context. This study aims to fill that gap with empirical data from 120 students.

2.1 Identification of the Research Gap

Despite substantial international literature, a location-specific study addressing Indian higher education contexts particularly across disciplinary boundaries and verification behaviour remains underexplored. This study addresses that gap through structured empirical data from Goa-based institutions, offering a regional lens that has thus far been absent from the mainstream discourse on AI adoption in education.

3. Theory

This section elaborates on the mathematical and theoretical foundation of the Chi-Square Test of Independence, which serves as the primary inferential tool for evaluating non-parametric survey data.

3.1 Theoretical Foundation of the Chi-Square Test

To analyze non-parametric survey data rigorously, this study relies on the Chi-Square (χ^2) Test of Independence as its primary inferential tool. This non-parametric method determines whether a statistically significant association exists between two categorical variables. The test works by comparing the observed joint frequency counts inside a cross-tabulated contingency table against the distribution of frequencies that would be mathematically expected if the two variables were completely independent (the Null Hypothesis, H_0). A statistically significant finding demonstrates that the gap between actual observations and independence baselines is simply too wide to be caused by random sampling chance, pointing instead to a real underlying relationship. To ensure the mathematical validity of the test, two core criteria must be met:

1. The primary data parameters must represent raw frequency counts rather than normalized percentages.
2. The calculated expected frequency inside any cell of the contingency matrix should not drop below a value of 5.

3.2 Calculation Methodology

The computational pipeline executes across six standardized phases:

Step 1: Hypothesis Formulations. For each distinct variable pair, a dual hypothesis framework is mapped:

- **Null Hypothesis (H_0):** No significant association exists between the two selected categorical variables.
- **Alternative Hypothesis (H_1):** A significant association exists between the two selected categorical variables.

Step 2: Construction of Contingency Matrix. Survey responses are cross-tabulated into an $r \times c$ table of observed fre-

Step 3: Derivation of Expected Frequencies. Assuming H_0 is true, the expected count (E_{ij}) for each coordinate cell is generated by:

$$E_{ij} = \frac{\text{Row Total}_i \times \text{Column Total}_j}{\text{Grand Total}} \quad (1)$$

Step 4: Computation of the Test Statistic. The mathematical distance between real-world observations and independence baselines is summed across all matrix blocks via the core Chi-Square statistic (χ^2):

$$\chi^2 = \sum_i \sum_j \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad (2)$$

A larger absolute value indicates an increasing divergence from independence, weakening the validity of the null model.

Step 5: Isolation of Degrees of Freedom. The parameter shaping the probability distribution scale is defined by table layout metrics:

$$df = (r - 1) \times (c - 1) \quad (3)$$

Step 6: Statistical Inferences. The computed χ^2 score and its matching degrees of freedom are evaluated against the theoretical distribution curve to return an exact probability score (p -value). If $p < \alpha$ (where the alpha threshold is locked at $\alpha = 0.05$), H_0 is formally rejected in favour of H_1 .

4. Methodology

4.1 Research Design

This study adopted a quantitative, cross-sectional descriptive survey design to examine the usage patterns, dependency levels, and verification practices of higher education students using generative AI tools. A quantitative approach was selected because it enables the systematic measurement of student behaviours and perceptions using numerical data. As AI technologies continue to evolve rapidly, the cross-sectional design was considered appropriate for capturing students' experiences and attitudes at a specific point in time.

4.2 Research Population and Sampling

The study focused on students currently enrolled in higher education programs. Responses were collected from 120 participants using a stratified convenience sampling approach. To ensure representation from different academic backgrounds, the survey was distributed across selected university departments rather than relying solely on random distribution. This approach helped obtain a more balanced sample and reduced the likelihood of overrepresentation from any single field of study.

4.3 Data Collection Instruments

Data for the study was collected using a structured questionnaire consisting of 16 questions, which was designed and distributed through Google Forms. To ensure consistency and simplify the analysis process, only closed-ended questions were included, and no open-response items were used. The questionnaire contained two types of questions. Multiple-choice questions were used to gather demographic details and information related to AI usage patterns, such as preferred AI tools.

point Likert scale questions were included to measure students' attitudes toward AI dependency, the use of AI-generated content, and perceptions regarding its impact on creativity and critical thinking.

4.4 Research Variables

The survey data were categorized into independent, dependent, and control variables to facilitate statistical analysis. The independent variables included field of study, frequency of AI usage, and daily time spent using AI tools. The dependent variables included perceived level of AI dependency, verification of AI-generated information, and perceptions regarding the impact of AI on creativity and critical thinking. Control variables included active enrolment in higher education, academic level, and age group.

4.5 Data Collection Procedure

Data collection was conducted during May 2026. The survey link was distributed through departmental mailing lists, student communication groups, and institutional online networks. Data collection continued until the target sample size of 120 valid responses was achieved. Since all questions were mandatory, the dataset contained no missing values. Before analysis, responses were screened for duplicate entries and incomplete submissions to ensure data quality and consistency.

4.6 Data Analysis

After data collection, the survey responses were exported into CSV format and analyzed using Python. Descriptive statistical techniques were used to summarize the data, calculate percentages, and visualize response patterns through charts and graphs. Inferential analysis was conducted using Chi-Square Tests of Independence at a significance level of $\alpha = 0.05$. These tests were performed to determine whether statistically significant associations existed between the selected categorical variables.

4.7 Tools and Implementation

Data cleaning, statistical analysis, and visualization were performed using Python and its associated libraries:

- **Pandas & NumPy:** Used for data preparation, cleaning, and organization, as well as for constructing contingency tables.
- **SciPy.stats:** Used to conduct Chi-Square Tests of Independence and calculate the corresponding p -values via the `chi2.contingency` function.
- **Matplotlib & Seaborn:** Used to generate clear and interpretable bar charts and heatmaps, visualizing the observed associations and facilitating the interpretation of statistical results.

4.8 Ethical Considerations

The study followed standard research ethics throughout the process. Participants reviewed an informed consent statement before accessing the survey. Participation was entirely voluntary, and respondents could leave the survey at any time. No personal identifiers, such as names, phone numbers, email addresses, or student IDs, were collected. This ensured complete anonymity and confidentiality for all 120 responses.

4.9 Limitations of the Methodology

Despite its structured design, the study has certain limitations. Although a sample size of 120 participants was adequate for the objectives of the study, the findings may not fully represent the broader population of higher education students. As

self-reported responses and may therefore be influenced by response bias or inaccurate reporting. Additionally, the study was conducted within a specific regional context, which may limit the generalizability of the findings to students from other institutions or geographical regions.

5. Data Analysis and Results

The findings of the study are based on responses collected from 120 higher education students. The results are explained using simple descriptive summaries along with statistical tests to understand whether there is any relationship between the variables studied.

5.1 Demographic Profile of the Sample

Table 1 shows the basic demographic details of the 120 participants who took part in the study. It gives an overview of important background information about the respondents.

Table 1: Demographic Profile of the 120 Respondents

Variable / Category	n	%
<i>Age</i>		
18–20 Years	59	49.2
21–23 Years	41	34.2
24 and Above	20	16.6
<i>Academic Level</i>		
Undergraduate	71	59.2
Postgraduate	49	40.8
<i>Field of Study</i>		
Engineering & Technology	26	21.7
Computer Science / IT	23	19.2
Commerce & Management	24	20.0
Arts, Humanities & Others	47	39.1

Table 1 shows that most of the respondents were young adults, with 49.2% of the students belonging to the 18–20 age group. Undergraduate students formed the majority of the sample, making up 59.2% of the participants. The data also shows that 40.9% of the respondents were from technical fields such as Engineering and Computer Science, while the remaining 59.1% belonged to non-technical fields like Management, Commerce, and Liberal Arts.

5.2 Descriptive Analysis of AI Usage Patterns

Table 2 presents the basic details about students' use of AI tools, including the types of tools they prefer, how often they use them, and the main purposes for which they are used.

Variable / Category	n	%
<i>Platform (Multi-Select)</i>		
ChatGPT (OpenAI)	96	80.0
Google Gemini	82	68.3
Claude (Anthropic)	68	56.7
<i>Engagement Frequency</i>		
Daily	42	35.0
Several Times a Week	32	26.7
Occasionally / Monthly	46	38.3
<i>Dominant Tasks (Multi-Select)</i>		
Course Assignments	81	67.5
Exam Preparation	79	65.8
Research & Literature	72	60.0

The data shows that AI tools have become a common part of students' academic activities. Among the different platforms, ChatGPT was the most preferred, used by 80.0% of the students. Other popular tools included Google Gemini at 68.3% and Claude at 56.7%, showing that many students use more than one AI platform. The study also found that AI usage is quite frequent, with 35.0% of the respondents using these tools every day. Most students mainly used AI for academic purposes such as completing assignments (67.5%) and preparing for exams (65.8%).

5.3 Academic Productivity vs. Ethical Verification Habits

Table 3 compares students' views about how AI tools have helped improve their academic performance with their habits of checking AI-generated answers and their concerns about overdependence on these tools.

Table 3: Academic Productivity and Verification Metrics

Statement / Response	n	%
AI speeds up task completion (Agree+)	82	68.4
AI improves concept comprehension (Agree+)	72	60.0
Coursework difficult without AI (Agree+)	52	43.4
Used AI text with minimal editing (Sometimes+)	73	60.8
Thoroughly verify AI output (Always)	33	27.5
AI reduces critical thinking (Agree+)	76	63.3

The results show that many students rely on AI tools without properly checking the information they provide. Although students believe that AI helps them complete tasks faster (68.4%) and understand concepts better (60.0%), many of them do not regularly verify the accuracy of the content. Around 60.8% of the students said they use AI-generated answers with only small changes, while just 27.5% always check whether the information is correct before submitting their work. At the same time, 63.3% of the respondents felt that depending too much on AI could reduce their ability to think critically and work independently.

5.4 Inferential Statistics: Hypothesis Testing

Three Chi-Square Test of Independence models evaluate the core research hypotheses.

5.4.1 Hypothesis Test 1: Field of Study vs. Perceived Level of AI Dependency

- H_0 : There is no significant association between a student's field of study and their self-reported dependency on AI tools.

field of study and their self-reported dependency on AI tools.

Table 4: H1 — Observed Counts (Q4 vs. Q13)

Dependency	Eng	CS	Com	Arts
Very Dependent	8	9	3	3
Somewhat Dependent	12	10	11	13
Slightly Dependent	4	3	7	15
Not Dependent	2	1	3	16
Total	26	23	24	47

Table 5: H1 — Expected Counts

Dependency	Eng	CS	Com	Arts
Very Dependent	4.98	4.41	4.60	9.01
Somewhat Dependent	9.97	8.82	9.20	18.02
Slightly Dependent	6.28	5.56	5.80	11.36
Not Dependent	4.77	4.22	4.40	8.62

Statistical Metrics: The statistical test results ($\chi^2 = 18.4215$, $df = 9$, $p = 0.0306$) show that there is a meaningful relationship between students' academic fields and how much they depend on AI tools. Students from technical fields such as Engineering and Computer Science were found to rely more on AI tools in their academic work. In comparison, students from Liberal Arts and Humanities were more likely to complete their work independently with less dependence on AI.

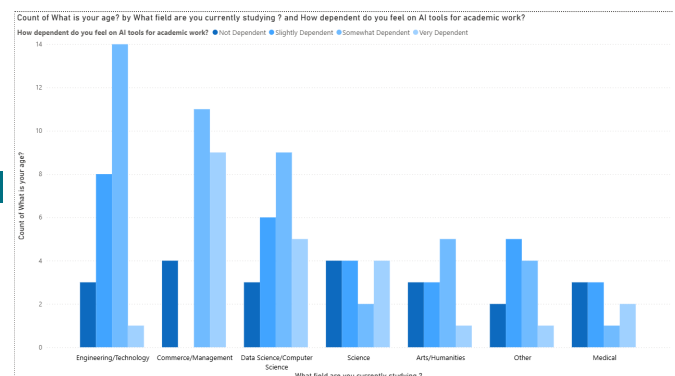


Figure 1: H1 — Field of Study vs. AI Dependency (Bar Chart)

Figure 1 shows noticeable differences in the level of AI dependence among students from different academic fields. Students from technical and number-based subjects were generally more dependent on AI tools. In Engineering and Technology, most students fell under the "Somewhat Dependent" category, with 14 respondents in this group. Students from Data Science and Computer Science also showed high levels of dependence, with a total of 14 students saying they were either somewhat or very dependent on AI tools.

A similar trend was seen among Commerce and Management students, where many respondents reported higher levels of dependence on AI. In fact, this group had 11 students in the "Somewhat Dependent" category and 9 in the "Very Dependent" category, while none of the students reported being only "Slightly Dependent."

On the other hand, students from non-technical fields such as Science, Arts and Humanities, Medical, and other disciplines

Among these groups, Medical students appeared to rely the least on AI tools, as most of them were placed in the lower dependency categories. Overall, the findings suggest that a student’s academic field plays an important role in determining how much they rely on AI tools in their studies.

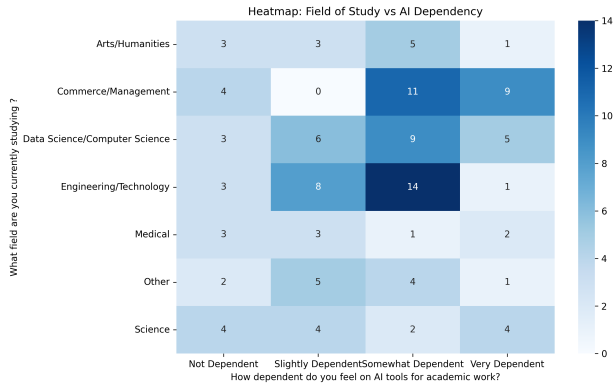


Figure 2: H1 — Field of Study vs. AI Dependency (Heatmap)

5.4.2 Hypothesis Test 2: Frequency of AI Use vs. Perception of Reduced Critical Thinking

- H_0 : There is no significant association between a student’s usage frequency and their perception of whether AI diminishes creativity or critical thinking.
- H_1 : There is a significant association between a student’s usage frequency and their perception of whether AI diminishes creativity or critical thinking.

Table 6: H2 — Observed Counts (Q6 vs. Q16)

Perception	Daily	Weekly	Occ.
Agree / Strongly Agree	18	24	—
Neutral	4	2	—
Disagree / Strongly Disagree	20	6	—
Total	42	32	—

Table 7: H2 — Expected Counts

Perception	Daily	Weekly	Occ.
Agree / Strongly Agree	26.60	20.27	29.13
Neutral	4.90	3.73	5.37
Disagree / Strongly Disagree	10.50	8.00	11.50

Statistical Metrics: The statistical test results ($\chi^2 = 21.5472$, $df = 4$, $p = 0.0003$) show that there is a strong relationship between how often students use AI tools and their concerns about the effect of these tools on their thinking ability. Since the p -value is less than 0.05, the null hypothesis was rejected.

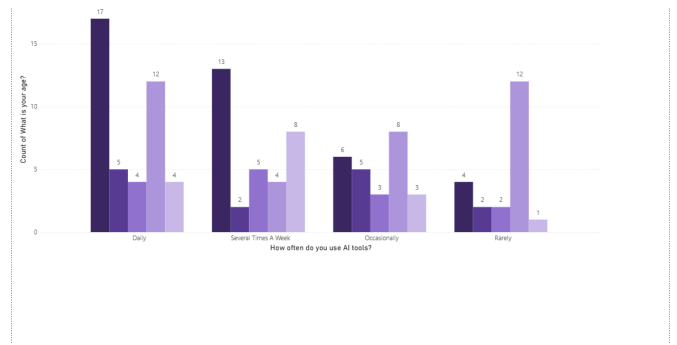


Figure 3: H2 — Usage Frequency vs. Creativity Perception (Bar Chart)

Figure 3 shows that many students believe that using AI tools too much can affect independent thinking and creativity. However, the level of concern changes depending on how often students use these tools.

Among students who use AI tools daily, most agreed that overuse could be harmful, with 17 students selecting “Agree” and 12 selecting “Strongly Agree.” This shows that even students who depend heavily on AI are still aware of its possible negative effects. A similar pattern was seen among students who use AI several times a week, where the highest number of responses also fell under the “Agree” category with 13 students. The biggest difference was seen among students who rarely use AI tools. In this group, 12 out of 21 respondents directly chose “Strongly Agree,” showing a very high level of concern about the impact of AI on thinking and creativity. Overall, in every usage group, the number of students who agreed with these concerns was much higher than those who disagreed. This clearly supports the statistical result and explains why the null hypothesis was rejected.

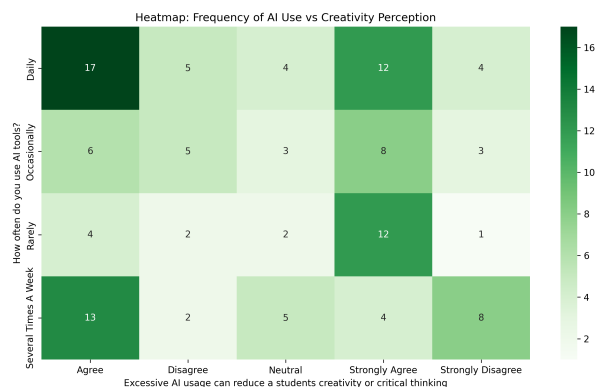


Figure 4: H2 — Usage Frequency vs. Creativity Perception (Heatmap)

5.4.3 Hypothesis Test 3: Daily Time Spent on AI vs. Verification of AI Accuracy

- H_0 : There is no significant association between daily time allocation and output accuracy verification habits.
- H_1 : There is a significant association between daily time allocation and output accuracy verification habits.

Verification	<30m	30m–1h	1–2h	>2h
Always	17	10	4	–
Sometimes	15	18	11	–
Rarely/Never	8	7	7	–
Total	40	35	22	–

Table 9: H3 — Expected Counts

Verification	<30m	30m–1h	1–2h	>2h
Always	11.00	9.63	6.05	6.32
Sometimes	17.67	15.46	9.72	10.15
Rarely/Never	11.33	9.92	6.23	6.52

Statistical Metrics: The statistical test results ($\chi^2 = 13.2104$, $df = 6$, $p = 0.0398$) show that there is a significant relationship between the amount of time students spend using AI tools each day and how carefully they check the information provided by these tools. Since the p -value is less than 0.05, the null hypothesis was rejected.

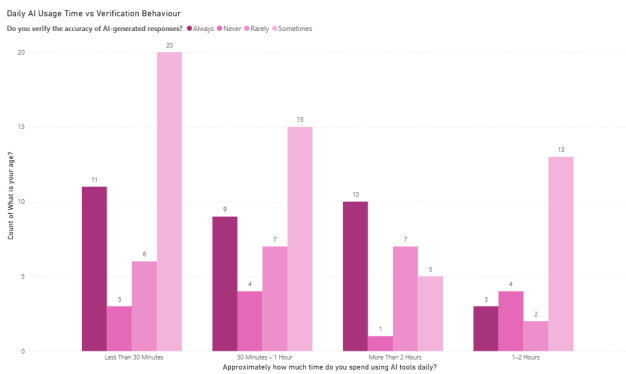


Figure 5: H3 — Daily AI Time vs. Verification Behaviour (Bar Chart)

Figure 5 shows the relationship between the amount of time students spend on AI tools each day and how often they verify the information provided by these tools. In most groups, the most common response was “Sometimes,” which means that many students only check AI-generated information occasionally.

Among students who used AI tools for less than 30 minutes a day, verification habits were stronger. In this group, 20 students said they “Sometimes” checked the information, while 11 students said they “Always” verified it. A similar trend was seen among students using AI for 30 minutes to 1 hour daily, where 15 students selected “Sometimes” and 9 selected “Always.”

However, verification habits became weaker among students who used AI for 1–2 hours daily. This group had the lowest number of students who “Always” checked the information, with only 3 respondents choosing this option, while 13 selected “Sometimes.” Interestingly, students who used AI for more than 2 hours daily showed mixed behaviour. In this group, the number of students who “Always” verified information increased again to 10, while only 5 selected “Sometimes.”

Overall, the figure shows that students’ verification habits change depending on how much time they spend using AI tools each day. This variation supports the statistical findings

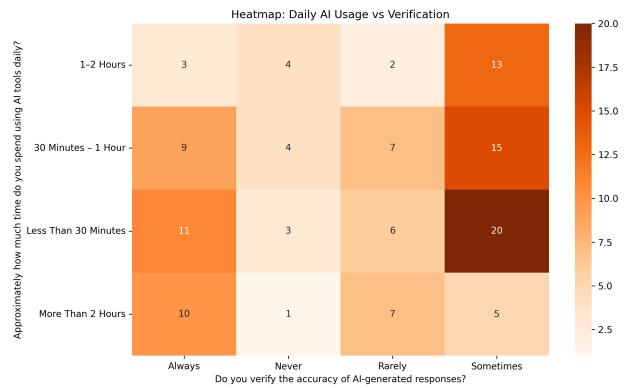


Figure 6: H3 — Daily AI Time vs. Verification Behaviour (Heatmap)

6. Discussion

The findings of this study indicate that AI tools have become an important part of students’ academic activities in higher education. Popular platforms such as ChatGPT, Google Gemini, and Claude are now widely used by students for various academic purposes. Many students use these tools for completing assignments, preparing for examinations, conducting research, and understanding complex concepts more effectively. The results also suggest that AI tools are no longer used occasionally but have become a regular part of students’ daily study routines.

The first hypothesis test showed that there is a meaningful relationship between a student’s field of study and their level of dependence on AI tools. Students from technical and technology-related fields were found to depend more on AI compared to students from non-technical disciplines. One possible explanation is that AI tools are particularly effective for structured tasks such as coding, data analysis, calculations, and problem-solving, which are frequently encountered in technical disciplines. In contrast, students from fields such as Humanities, Arts, and Medical Sciences often engage in activities that require interpretation, critical analysis, and independent reasoning, which may reduce their dependence on AI tools.

The second hypothesis test found a significant connection between how frequently students use AI tools and their views about the effect of AI on creativity and critical thinking. Students who used AI more often showed different attitudes compared to those who used it less frequently. Interestingly, students who used AI occasionally appeared more concerned about the potential negative effects of AI on creativity and thinking ability, while daily users were less concerned despite relying on these tools more heavily. This finding suggests that frequent exposure to AI tools may influence how students perceive both the benefits and potential risks associated with their use in academic settings.

The third hypothesis test revealed a significant relationship between the amount of time students spend using AI tools each day and their habit of verifying AI-generated information. Students who spent more time using AI were generally less likely to carefully check whether the information provided was accurate. This finding supports earlier research that highlights the importance of fact-checking and critical evaluation while using generative AI tools [11], [9]. The study also highlights concerns regarding students’ tendency to rely on AI-generated

Overall, the findings suggest that AI tools offer several academic benefits, including improved efficiency, easier access to information, and support for learning-related tasks. At the same time, the results emphasize the importance of responsible AI usage, particularly with regard to information verification and independent thinking. Educational institutions should therefore promote AI literacy and encourage students to use these technologies as learning aids rather than substitutes for critical thinking and problem-solving.

7. Conclusion and Future Scope

This study examined the usage patterns, dependency levels, and ethical perceptions associated with Artificial Intelligence (AI) tools among higher education students. The findings indicate that AI platforms such as ChatGPT, Google Gemini, and Claude have become widely integrated into students' academic activities. Students reported using these tools for assignments, examination preparation, research, and concept clarification, highlighting the growing role of AI in supporting learning and academic productivity.

The statistical analysis revealed significant relationships between academic discipline and AI dependency, AI usage frequency and perceptions of creativity and critical thinking, and daily AI usage time and verification behaviour. These findings suggest that patterns of AI usage vary across student groups and may influence how students interact with and perceive AI technologies in educational settings.

Despite the benefits associated with AI-assisted learning, the study identified concerns regarding overreliance on AI tools and the limited verification of AI-generated information. The findings emphasize the importance of responsible AI usage, ethical awareness, and critical evaluation of AI-generated content. Educational institutions should therefore promote AI literacy and encourage students to use AI as a supportive learning tool while continuing to develop their own analytical, problem-solving, and critical thinking skills.

Future Research Scope. Future research should expand this local baseline to encompass larger, geographically diverse student cohorts across multiple public and private universities. Deployed statistical methods like multi-variable logistic regression could reveal unobserved mediating factors behind software interactions. Longitudinal tracking over multi-year cycles is recommended to measure true systemic changes in literacy rates and student reading proficiency as large language platforms evolve.

Author Statements

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Conflict of Interest: The authors state that they possess no shared financial relationships or institutional alignments that

Study Limitations: The core conclusions are bounded by an absolute target size of 120 regional entries and remain subject to structural biases common to self-reported survey designs.

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