



Generative AI Adoption and Usage Patterns Among College Students in Vijayawada, India

Savanam Chandra Sekhar ^{1*}, Anshita Golla ²

¹⁻² KL Business School, Koneru Lakshmaiah Education Foundation (KL University), Vaddeswaram, Guntur, Andhra Pradesh 522302, India

* Corresponding Author: Savanam Chandra Sekhar

Article Info

ISSN (online): 3107-3972

Volume: 03

Issue: 05

Received: 14-08-2026

Accepted: 16-09-2026

Published: 19-10-2026

Page No: 38-49

Abstract

The rapid adoption of generative artificial intelligence (GenAI) in higher education has transformed the ways students access information and undertake academic activities. This study examines the adoption and usage patterns of artificial intelligence (AI) tools among college students at KL University, Vijayawada, with particular attention to ChatGPT, Google Gemini, and Microsoft Copilot. A quantitative, descriptive, cross-sectional research design was employed using 132 usable student responses obtained through convenience sampling. Data were analysed using frequencies, percentages, and descriptive cross-tabulations to examine demographic and academic characteristics, AI-tool selection, and frequency of use. The findings show that ChatGPT was the most widely reported AI tool, used by 95.5% of respondents, followed by Google Gemini (43.2%), other AI tools (34.1%), and Microsoft Copilot (9.1%). Overall, 72.7% of respondents reported using AI tools often or very often for academic purposes. A descriptive comparison indicated higher frequent use among female respondents (80.0%) than male respondents (57.1%). The sample was predominantly composed of students aged 18–20 years, females, BBA students, and third-year students. The findings establish that AI use is widespread and relatively frequent within the surveyed sample. However, the available dataset does not contain the academic-outcome measures required to determine whether AI use improves or reduces academic performance. The study therefore focuses on AI adoption and usage behaviour rather than causal academic effects and highlights the need for future research combining AI-use measures with reliable academic-performance indicators.

DOI: <https://doi.org/10.54660/GMPJ.2026.3.5.38-49>

Keywords: AI adoption, ChatGPT, Google Gemini, Microsoft Copilot, Higher education

1. Introduction

Artificial intelligence (AI) has evolved rapidly from specialised applications in higher education to widely accessible tools supporting information retrieval, content generation, writing, translation, coding, problem solving, summarisation, and personalised learning. The emergence of generative artificial intelligence (GenAI), particularly conversational systems capable of producing human-like responses, has further transformed students' interaction with academic information and learning resources. While earlier research focused on applications such as intelligent tutoring, assessment, profiling, prediction, and adaptive learning, recent scholarship has increasingly examined GenAI in relation to teaching, learning, assessment, and academic integrity (Zawacki-Richter *et al.*, 2019; Castillo-Martínez *et al.*, 2024; Yusuf *et al.*, 2024) ^[6, 28, 29].

The accessibility of GenAI presents both opportunities and challenges for university students. AI assistants can provide immediate explanations, examples, writing support, programming assistance, translation, and personalised academic guidance.

However, concerns regarding inaccurate or fabricated information, excessive dependence, reduced independent reasoning, privacy, and academic misconduct have also emerged (Chan & Hu, 2023; Baig & Yadegaridehkordi, 2024) ^[3, 7]. Thus, the educational significance of AI depends not simply on whether students use it, but on which tools they use, how frequently they use them, and the contexts in which they are employed.

Among the expanding range of GenAI applications, ChatGPT, Google Gemini, and Microsoft Copilot have become relevant to students' academic activities. These tools can support question answering, explanation, summarisation, brainstorming, writing, language assistance, coding, and other academic tasks. Nevertheless, their availability does not by itself demonstrate improved academic achievement. AI-generated responses may contain factual inaccuracies, incomplete reasoning, or fabricated information, making critical evaluation and verification essential (Eke, 2023; Baig & Yadegaridehkordi, 2024) ^[3, 11].

Evidence concerning the relationship between GenAI and academic outcomes is also mixed and context-dependent. Recent meta-analyses and experimental research indicate that AI-supported learning can produce positive effects under appropriate instructional and assessment conditions, but outcomes vary according to learning objectives, task characteristics, intervention design, and patterns of student engagement (Sun & Zhou, 2024a; Deng *et al.*, 2025) ^[10, 21]. Consequently, AI adoption and AI impact should be treated as distinct empirical questions. Measuring the frequency of AI use can establish adoption behaviour, but cannot independently demonstrate whether such use improves or reduces academic performance.

The Indian higher-education context provides an important setting for examining these developments as universities increasingly integrate digital and AI-enabled resources into academic activities. Understanding which AI tools students select and how frequently they use them can provide useful evidence for educators and institutional decision-makers concerned with AI literacy, responsible use, academic integrity, and assessment practices.

Against this background, the present study examines AI-tool adoption and usage among college students at KL University, Vijayawada, with particular attention to ChatGPT, Google Gemini, Microsoft Copilot, and other AI tools. The study analyses students' age, gender, course, year of study, AI-tool selection, and frequency of AI use for academic purposes. These variables provide a descriptive basis for examining the extent and distribution of AI adoption and for comparing usage patterns across available demographic and academic categories.

An important methodological consideration is the measurement of academic outcomes. Although the original questionnaire included questions intended to capture academic performance and related outcomes, the response dataset available for analysis does not contain the corresponding item-level responses. Therefore, the present study is restricted to AI adoption and usage behaviour and does not statistically establish relationships between AI use and academic performance, learning experience, assignment quality, productivity, or related outcomes. This distinction prevents unsupported causal interpretation and defines the empirical scope of the study.

Accordingly, the study contributes institution-specific evidence on student AI adoption and usage patterns rather

than an estimate of the academic impact of individual AI tools. By documenting students' demographic and academic profiles, preferred AI tools, and frequency of use, the study provides a behavioural foundation for future research incorporating reliable academic-performance measures. Such research can subsequently examine whether, and under what conditions, AI-assisted academic practices contribute to measurable learning and performance outcomes.

2. Literature Review

Artificial intelligence (AI) has evolved from specialised applications such as intelligent tutoring, adaptive learning, assessment, and student profiling to generative AI (GenAI) systems capable of producing text, explanations, summaries, code, and other academic content. Consequently, higher-education research now encompasses both established AI applications and the rapidly expanding literature on conversational GenAI tools such as ChatGPT, Google Gemini, and Microsoft Copilot.

2.1. AI in Higher Education

Zawacki-Richter *et al.* (2019) ^[29] provided an early systematic review of AI applications in higher education, identifying assessment and evaluation, adaptive systems and personalisation, profiling and prediction, and intelligent tutoring as major application areas. The review also highlighted limited educator involvement and called for greater attention to pedagogical and ethical dimensions of AI adoption. These issues have become increasingly important as AI moves from experimental applications toward routine academic use.

The emergence of GenAI has considerably broadened this research agenda. Baig and Yadegaridehkordi (2024) ^[3], in a systematic review of ChatGPT in higher education, identified applications involving students, educators, researchers, and other university stakeholders, alongside growing research on adoption, educational use, academic integrity, and assessment. Bhullar *et al.* (2024) ^[4], through bibliometric analysis, similarly identified academic integrity, student learning, engagement, examinations, and research as prominent themes. Together, these studies demonstrate that AI adoption is simultaneously a technological, behavioural, educational, institutional, and ethical phenomenon.

2.2. Student Adoption and Use of Generative AI

Student adoption of GenAI is shaped by perceived usefulness, accessibility, confidence, and concerns regarding reliability and ethical use. Chan and Hu (2023) ^[7], studying 399 undergraduate and postgraduate students across six Hong Kong universities, found generally positive perceptions of GenAI for personalised learning, writing, brainstorming, research, and analytical activities, while students also expressed concerns about accuracy, privacy, ethics, and possible effects on learning.

These findings indicate the importance of examining actual usage behaviour in addition to attitudes and intentions. Students may express favourable perceptions without frequent use, while others may use AI extensively despite reservations about its reliability. Baig and Yadegaridehkordi (2024) ^[3] further noted that ChatGPT is used for diverse academic purposes, including explanation, content generation, language support, programming, idea development, and writing. Thus, the present study focuses on

observable adoption and frequency patterns rather than relying solely on perceptions.

2.3. Generative AI and Academic Achievement

Whether GenAI improves academic achievement remains an empirical question requiring appropriate outcome measures. Sun and Zhou (2024b) ^[22], in a meta-analysis of 28 articles comprising 65 independent studies and 1,909 participants, reported evidence of positive contributions of GenAI to college students' academic achievement while highlighting the importance of contextual and moderating conditions.

Deng *et al.* (2025) ^[10] synthesised 69 experimental studies and found positive effects of ChatGPT on academic performance, affective-motivational outcomes, and higher-order thinking propensities. However, they also identified methodological limitations concerning assessment design, statistical power, and post-intervention measurement, emphasising the need for rigorous research designs and objective assessment.

Similarly, Chen and Cheung (2025) ^[8], analysing 57 studies and 97 effect estimates involving university students, reported positive effects of GenAI on overall learning outcomes, including academic achievement, affective-motivational outcomes, higher-order thinking, and language skills. Nevertheless, effect sizes varied according to learner characteristics, intervention duration, subject area, assessment type, and contextual conditions. Almasri (2025) ^[1] likewise demonstrated through a meta-analysis of 29 empirical studies that the relationship between AI and academic achievement varies according to educational level, AI role, intervention duration, learning strategy, subject area, and AI type. These findings collectively suggest that AI availability or usage frequency alone cannot establish academic impact.

2.4. Generative AI, Engagement and Cognitive Outcomes

Research has also examined engagement and cognitive outcomes beyond conventional academic achievement. Recent systematic evidence indicates positive effects of ChatGPT-based learning on overall student engagement, particularly cognitive engagement, while recognising the possibility of disengagement associated with excessive reliance on AI. Similarly, Essel *et al.* (2024) ^[12], using an experimental design involving 125 university students in Ghana, examined the effects of ChatGPT on critical, creative, and reflective thinking. Their findings illustrate that GenAI may influence cognitive development when incorporated into structured learning activities.

However, the educational consequences of GenAI remain context-dependent. Outcomes may vary with the nature of the task, instructional design, student engagement, prompt quality, accuracy of AI outputs, and students' ability to critically evaluate generated information. Thus, the literature supports a conditional rather than automatic relationship between GenAI use and educational outcomes.

2.5. Risks, Academic Integrity and Responsible Use

Academic integrity is among the most prominent concerns associated with GenAI in higher education. AI systems can generate essays, answers, summaries, and other academic materials, creating challenges in distinguishing independent student work from AI-assisted production. Academic integrity has consequently emerged as a major theme in both

the systematic review of Baig and Yadegaridehkordi (2024) ^[3] and the bibliometric analysis of Bhullar *et al.* (2024) ^[4].

Reliability and ethical use are additional concerns. Chan and Hu (2023) ^[7] reported that students recognised problems related to accuracy, privacy, and ethics, highlighting the need for students to verify AI-generated information and exercise independent judgement. Accordingly, responsible GenAI use depends on the interaction among the student, AI tool, academic task, instructional environment, and assessment approach, rather than on frequency of use alone.

2.6. Research Gap

The literature establishes substantial research on GenAI adoption, perceptions, academic integrity, engagement, cognitive outcomes, and academic achievement. Nevertheless, three gaps are particularly relevant to the present study. First, research has predominantly focused on ChatGPT, with comparatively less institution-specific evidence on students' use of other major tools such as Google Gemini and Microsoft Copilot. Second, many studies examine structured interventions or educational effects rather than documenting actual AI adoption and usage patterns within a specific university. Third, although recent meta-analyses report generally positive educational effects, these effects vary considerably across learners, disciplines, tasks, interventions, and assessment contexts.

The present study addresses this descriptive and institutional gap by examining AI adoption and usage among students at KL University, Vijayawada, with particular attention to demographic and academic characteristics, AI-tool selection, and frequency of use. Importantly, the study distinguishes AI adoption behaviour from academic-performance outcomes. Because academic-performance responses are unavailable in the supplied dataset, the study does not test causal or outcome-based effects of AI use. Instead, it establishes an empirical profile of student AI adoption that can support future outcome-oriented research.

2.7. Objectives of the Study

The study aims to examine AI-tool adoption and usage patterns among college students at KL University, Vijayawada. Specifically, it seeks to (i) describe the demographic and academic profile of respondents in terms of age, gender, course, and year of study; (ii) identify the AI tools used for academic purposes, particularly ChatGPT, Google Gemini, and Microsoft Copilot; (iii) assess the frequency of AI-tool use for academic activities; (iv) examine variations in AI-adoption and usage patterns across available demographic and academic categories; and (v) provide a foundation for future research examining the relationship between AI use and academic outcomes using appropriate performance measures.

2.8. Research Questions

The study seeks to understand the demographic and academic profile of the surveyed students at KL University, Vijayawada, the AI tools they select for academic purposes, and the frequency with which these tools are used. It further examines whether AI-tool usage patterns vary across students based on age, gender, course, and year of study. In addition, the study considers what academic-outcome measures would be required in future research to determine whether AI-tool usage is associated with students' academic performance.

2.9. Hypotheses of the Study

Based on the categorical variables available in the dataset, the following hypotheses are proposed:

H1: There is a significant association between gender and frequency of AI-tool use among college students.

H2: There is a significant association between academic course and frequency of AI-tool use among college students.

H3: There is a significant association between year of study and frequency of AI-tool use among college students.

H4: There is a significant association between age group and frequency of AI-tool use among college students.

H5: There is a significant association between the breadth of

AI-tool adoption and frequency of AI-tool use among college students.

These hypotheses concern AI-adoption behaviour rather than academic achievement. Hypotheses asserting that AI use improves or reduces academic performance are not empirically testable with the current dataset because corresponding academic-outcome variables are unavailable.

2.10. Conceptual Framework

The conceptual framework in Figure 1 distinguishes contextual characteristics, AI adoption, AI usage behaviour, and potential academic outcomes.

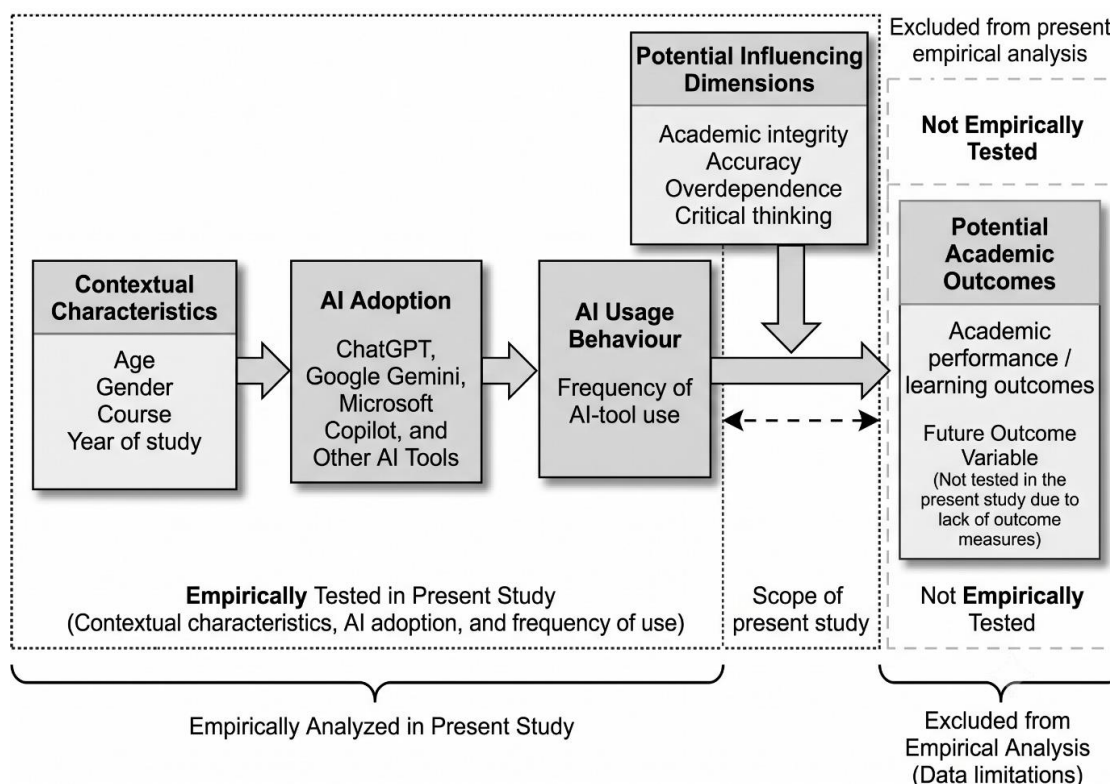


Fig 1: Conceptual framework

Academic integrity, information accuracy, overdependence, and critical-thinking requirements may influence the relationship between AI use and educational outcomes.

For the present study, empirical analysis is restricted primarily to contextual characteristics, AI adoption, and frequency of use, because the available response dataset does not contain the academic-outcome measures required to test the final relationship.

3. Research Methodology

3.1. Research Design

The study adopted a quantitative, descriptive, and cross-sectional research design to examine AI-tool adoption and usage patterns among college students at KL University, Vijayawada. The quantitative approach enabled systematic analysis of categorical survey responses using frequencies, percentages, and cross-tabulations. The cross-sectional design captured students' AI-use behaviour at a particular point in time without manipulating the study environment (Creswell & Creswell, 2018; Saunders *et al.*, 2019; Sekaran & Bougie, 2016) [9, 18, 19].

3.2. Population and Sampling

The target population comprised college students at KL University, Vijayawada. The final analytical sample consisted of 132 usable responses ($n = 132$). A convenience sampling approach was used because the available survey records did not establish probability-based participant selection. Consequently, the findings describe the surveyed respondents and should not be generalised to the entire university student population without appropriate caution.

3.3. Data Collection and Research Instrument

Primary data were obtained through a structured questionnaire administered to college students. The variables available for the present analysis were age, gender, course of study, year of study, AI tools used for academic purposes, and frequency of AI-tool use. The questionnaire also contained, or was intended to contain, questions concerning academic outcomes and AI-related concerns; however, the corresponding item-level responses were not available in the dataset used for this analysis. Therefore, no missing academic-outcome responses were imputed or inferred.

3.4. Data Processing and Statistical Analysis

The responses were organised and analysed using descriptive statistical techniques. Frequencies and percentages were calculated for demographic, academic, and AI-use variables. AI-tool adoption was treated as a multiple-response variable, since respondents could select more than one AI tool; therefore, tool-specific percentages do not necessarily sum to 100%.

Cross-tabulation was used to examine differences in AI-use frequency across demographic categories, particularly gender. Where inferential testing is undertaken, chi-square analysis is appropriate for assessing associations between categorical variables, subject to the adequacy of expected cell frequencies. The analysis focuses on AI adoption and usage behaviour and does not infer academic-performance effects from variables that were not available.

3.5. Reliability and Validity

Because the available dataset does not contain the item-level responses for the proposed academic-performance and concern-related scales, their internal consistency could not be recalculated. Accordingly, no unsupported reliability coefficients are reported. Future research should retain item-level responses to permit assessment of internal consistency and construct validity using established procedures (Bonett & Wright, 2015; Taber, 2018) ^[5, 23]. Questionnaire content should also be reviewed by subject experts and pilot-tested before subsequent data collection.

3.6. Ethical Considerations

Participation in the survey was intended to be voluntary, with respondents informed of the academic purpose of the study. The analysis excludes personal identifiers and reports results in aggregate form. The collected data should be stored securely and used only for legitimate academic and research purposes.

3.7. Methodological Scope and Limitations

The methodology supports an empirical description of AI-tool adoption and frequency among the 132 surveyed students. However, the convenience sampling procedure and cross-sectional design restrict generalisability and prevent causal interpretation. More importantly, the supplied dataset does not contain responses measuring academic performance, learning experience, assignment quality, productivity, or AI-related concerns. Consequently, the present study establishes patterns of AI adoption and usage, but cannot statistically establish whether Gemini, Microsoft Copilot, or other AI tools improve or reduce students' academic performance. Future research should collect matched AI-use and academic-outcome measures to test this relationship directly.

4. Results

4.1. Demographic and Academic Profile of Respondents

The final analysis comprised 132 usable responses. Table 1 presents the demographic and academic characteristics of the respondents.

Table 1: Demographic and academic profile of respondents (n = 132)

Variable	Category	Frequency	Percentage (%)
Age	Below 18	3	2.3
	18–20	93	70.5
	21–23	27	20.5
	Above 23	9	6.8
Gender	Female	90	68.2
	Male	42	31.8
Course	BBA	69	52.3
	B.Tech	30	22.7
	B.Com	12	9.1
	MBA	6	4.5
	Other	15	11.4
Year of study	1st Year	3	2.3
	2nd Year	9	6.8
	3rd Year	114	86.4
	4th Year	6	4.5
Total		132	100.0

The respondent profile is concentrated within the younger age categories. Students aged 18–20 constitute the largest group, with 93 respondents (70.5%), followed by those aged 21–23 with 27 respondents (20.5%). Students above 23 years account for 9 respondents (6.8%), while 3 respondents (2.3%) are below 18 years. Thus, the sample primarily represents traditionally aged college students.

Female respondents constitute 90 (68.2%) of the sample, compared with 42 male respondents (31.8%). In terms of academic programme, BBA students form the largest group (69; 52.3%), followed by B.Tech students (30; 22.7%). B.Com students account for 12 respondents (9.1%), MBA students for 6 (4.5%), and students enrolled in other programmes for 15 (11.4%).

The year-of-study distribution is highly concentrated in the third year. Third-year students account for 114 respondents (86.4%), followed by second-year students (9; 6.8%), fourth-year students (6; 4.5%), and first-year students (3; 2.3%). Accordingly, the descriptive findings primarily reflect respondents who are 18–20 years old, female, enrolled in BBA, and studying in the third year.

4.2. AI-Tool Adoption for Academic Purposes

Respondents could select more than one AI tool used for academic purposes. Accordingly, AI-tool adoption was analysed as a multiple-response variable. The percentages reported in Table 2 represent the proportion of respondents selecting each tool and therefore do not sum to 100%.

Table 2: AI tools used for academic purposes (multiple response)

AI Tool	Respondents Selecting Tool	Percentage of Respondents (%)
ChatGPT	126	95.5
Google Gemini	57	43.2
Other AI tools	45	34.1
Microsoft Copilot	12	9.1

ChatGPT is the most frequently reported AI tool, selected by 126 respondents (95.5%). Google Gemini is the second most frequently reported tool, selected by 57 respondents (43.2%), followed by other AI tools (45; 34.1%). Microsoft Copilot is reported by 12 respondents (9.1%).

These findings indicate substantial adoption of ChatGPT within the surveyed sample, while Gemini also has considerable usage. Copilot has comparatively limited adoption among these respondents. Because multiple

selections were permitted, the percentages represent tool-level adoption rather than mutually exclusive market shares. The results therefore describe the prevalence of reported use but do not establish differences in effectiveness, academic outcomes, or user satisfaction across tools.

4.3. Frequency of AI-Tool Use for Academic Purposes

Table 3 presents the reported frequency with which respondents use AI tools for academic purposes.

Table 3: Frequency of AI-tool use for academic purposes

Frequency Category	Frequency	Percentage (%)
Rarely	3	2.3
Sometimes	33	25.0
Often	57	43.2
Very Often	39	29.5
Total	132	100.0

The most frequently reported category is “Often,” selected by 57 respondents (43.2%), followed by “Very Often,” selected by 39 respondents (29.5%). Together, these categories comprise 96 respondents (72.7%), indicating that nearly three-quarters of the sample report relatively frequent academic use of AI tools.

A further 33 respondents (25.0%) report using AI tools sometimes, while only 3 (2.3%) report rare use. The distribution therefore indicates that AI tools are regularly used for academic purposes by a substantial proportion of the

surveyed students. However, frequency of use is a behavioural measure and, in the absence of academic-outcome variables, cannot be interpreted as evidence of improved or reduced academic performance.

4.4. AI-Tool Use Frequency by Gender

To examine descriptive differences in AI-use frequency between female and male respondents, a cross-tabulation was prepared. Table 4 reports both frequencies and percentages calculated within each gender category.

Table 4: Frequency of AI-tool use by gender

Gender	Rarely	Sometimes	Often	Very Often	Total
Female	0 (0.0%)	18 (20.0%)	45 (50.0%)	27 (30.0%)	90 (100.0%)
Male	3 (7.1%)	15 (35.7%)	12 (28.6%)	12 (28.6%)	42 (100.0%)
Total	3	33	57	39	132

Note: Percentages in parentheses are calculated within gender.

Descriptive differences are evident in the distribution of AI-use frequency across gender groups. Among female respondents, 45 (50.0%) report using AI tools often and 27 (30.0%) report very frequent use. Thus, 72 of the 90 female respondents (80.0%) fall within the “Often” or “Very Often” categories.

Among male respondents, 12 (28.6%) report using AI tools often and 12 (28.6%) report very often. Consequently, 24 of the 42 male respondents (57.1%) fall within the two higher-frequency categories. Male respondents also show higher proportions in the “Sometimes” (35.7%) and “Rarely” (7.1%) categories.

The cross-tabulation therefore indicates a descriptive difference in AI-use frequency by gender within this sample.

However, these percentages alone do not establish statistical significance. A chi-square test would be required to determine whether gender and AI-use frequency are statistically associated, provided that the expected cell-frequency assumptions are adequately satisfied. Accordingly, the present results do not make an inferential claim regarding gender differences.

4.5. Availability of Academic-Outcome Variables

The broader study framework concerns AI use and academic outcomes. Therefore, a data-availability assessment was undertaken before attempting outcome-based statistical analysis.

Table 5: Availability of proposed academic-outcome variables

Expected Research Variable	Present in Supplied Response Data?	Treatment in Present Analysis
Academic performance	No	Not statistically tested
Learning experience	No	Not statistically tested
Assignment quality	No	Not statistically tested
Productivity / time saving	No	Not statistically tested
Academic-integrity concerns	No	Not statistically tested
Accuracy / critical-thinking concerns	No	Not statistically tested
Age	Yes	Analysed
Gender	Yes	Analysed
Course	Yes	Analysed
Year of study	Yes	Analysed
AI tools used	Yes	Analysed
Frequency of AI use	Yes	Analysed

The available response data contain six variables suitable for the present empirical analysis: age, gender, course, year of study, AI-tool adoption, and frequency of AI-tool use. The item-level responses required to measure academic performance, learning experience, assignment quality, productivity, and AI-related concerns are not available in the supplied dataset.

This limitation is particularly important because the study cannot validly estimate relationships between AI use and academic outcomes without corresponding outcome measures. Consequently, the present results are restricted to describing respondent characteristics, AI-tool adoption, and

AI-use frequency. No means, correlations, regression coefficients, causal effects, or hypothesis decisions concerning academic performance are reported from unavailable variables.

4.6. Alignment with Research Objectives and Hypotheses

The results directly address the descriptive objectives concerning respondent characteristics, AI-tool adoption, and frequency of academic AI use. The available data also permit a descriptive cross-tabulation of AI-use frequency by gender.

Table 6: Alignment of hypotheses with available evidence

Hypothesis	Variables	Evidence Available	Present Status
H1	Gender × AI-use frequency	Complete cross-tabulation available	Descriptively examined; inferential test not reported
H2	Course × AI-use frequency	Complete cross-tabulation unavailable	Not tested
H3	Year of study × AI-use frequency	Complete cross-tabulation unavailable	Not tested
H4	Age group × AI-use frequency	Complete cross-tabulation unavailable	Not tested
H5	Breadth of AI adoption × frequency	Respondent-level multi-tool combinations unavailable	Not tested

The available evidence therefore supports descriptive conclusions regarding the composition of the sample, the prevalence of AI-tool adoption, and the frequency of academic AI use. The gender cross-tabulation identifies a descriptive difference in usage frequency, but statistical significance cannot be established without an inferential test. The remaining hypotheses cannot be tested from marginal frequency distributions because the respondent-level cross-tabulated observations required for those analyses are not available. In particular, the multiple-response tool-adoption data do not provide sufficient respondent-level information to construct a valid measure of individual breadth of AI adoption.

4.7. Summary of Major Findings

The descriptive analysis is based on 132 usable responses from college students. The sample is predominantly composed of students aged 18–20 years (70.5%), female respondents (68.2%), BBA students (52.3%), and third-year students (86.4%). ChatGPT is the most widely reported AI tool, selected by 95.5% of respondents, followed by Google Gemini (43.2%), other AI tools (34.1%), and Microsoft Copilot (9.1%). Since respondents could select multiple AI tools, these percentages are not mutually exclusive and should not be interpreted as market shares. Overall, 72.7% of respondents reported using AI tools either “Often” or “Very Often” for academic purposes. The gender cross-tabulation

further showed that 80.0% of female respondents and 57.1% of male respondents reported AI use in these two higher-frequency categories; however, this difference is descriptive and should not be interpreted as statistically significant without an appropriate inferential test. Importantly, the available dataset does not contain the item-level responses required to measure academic performance, learning experience, assignment quality, productivity, or AI-related concerns. Therefore, the findings provide evidence of AI adoption and usage behaviour but do not establish whether AI tools improve or reduce academic performance. These findings should also be interpreted in light of the study's methodological limitations, including convenience sampling, a cross-sectional design, a concentrated respondent profile, and the incomplete availability of proposed outcome variables.

5. Discussion

The present study examined AI-tool adoption and usage patterns among college students at KL University, Vijayawada, using a quantitative, descriptive, cross-sectional design. The findings indicate a high level of engagement with artificial intelligence (AI) tools for academic purposes, with particularly strong adoption of ChatGPT and frequent use of AI tools among the surveyed students. These findings are consistent with the rapidly expanding role of generative artificial intelligence (GenAI) in higher education, where

recent research has documented increasing student adoption, diversification of AI-supported academic activities, and growing institutional attention to AI literacy, assessment, and academic integrity (Baig & Yadegaridehkordi, 2024; Jo, 2024; Stohr *et al.*, 2024) ^[3, 14, 20].

Importantly, the present study distinguishes between AI adoption and AI impact. Although recent experimental and meta-analytic evidence suggests that appropriately designed GenAI interventions can produce positive learning outcomes, the present dataset does not contain academic-performance or learning-outcome measures. Therefore, the findings reported here should be interpreted as evidence of students' AI-use behaviour rather than evidence that AI improves or reduces academic achievement.

5.1. Predominance of Younger Students and the Context of AI Adoption

The demographic profile shows that 70.5% of respondents are aged 18–20 years and a further 20.5% are aged 21–23 years. Thus, more than 90% of the sample is below 24 years of age. This concentration is consistent with the study's university-student population but also indicates that the findings primarily reflect the behaviour of traditionally aged college students.

Recent research suggests that student characteristics can influence patterns of AI adoption and use. Baek *et al.* (2024) ^[2], for example, found that age, gender, academic major, institutional characteristics, and institutional policy were associated with different forms of ChatGPT use among U.S. college students. Similarly, Stohr *et al.* (2024) ^[20], using data from 5,894 students across Swedish universities, reported differences in AI-chatbot usage according to demographic and academic characteristics.

The concentration of younger respondents in the present study therefore provides an appropriate context for examining emerging student AI practices but limits comparisons across age groups. Only 3 respondents (2.3%) are below 18 years and 9 (6.8%) are above 23 years. Consequently, the available data do not provide sufficiently balanced age categories for meaningful age-based inferential comparisons. The present findings should therefore be interpreted as describing the surveyed student population rather than establishing age-related differences in AI adoption.

5.2. Gender Composition and Differences in AI-Use Frequency

Female respondents constitute 68.2% of the sample, compared with 31.8% male respondents. The gender distribution is therefore substantially unbalanced. The cross-tabulation nevertheless reveals an interesting descriptive pattern: 80.0% of female respondents report using AI tools either often or very often, compared with 57.1% of male respondents.

This finding is noteworthy because recent international evidence has identified gender differences in AI-chatbot engagement, although the direction of those differences is not uniform across studies or contexts. Stohr *et al.* (2024) ^[20] found significant gender differences in chatbot usage and attitudes among Swedish university students, with male students generally reporting greater usage and more positive attitudes. Similarly, Møgelvang *et al.* (2024) ^[17], based on a Norwegian higher-education sample of 2,692 students, found

that male students reported more frequent engagement with GenAI chatbots across a broader range of applications.

The descriptive pattern in the present study therefore differs from some recent European evidence, since female respondents show a greater proportion of frequent AI use. This difference should not be interpreted as contradictory evidence about gender and AI adoption in general. Rather, it suggests that gender-related patterns may be context-dependent and influenced by institutional, disciplinary, cultural, or sample-composition factors.

Moreover, the present study does not report a chi-square test of gender and AI-use frequency. Therefore, the observed difference cannot be described as statistically significant. The cross-tabulation establishes only that the distribution of reported usage frequency differs descriptively between the female and male groups. Future research using a larger and more balanced sample should formally test gender differences while controlling for course, year of study, prior digital experience, and institutional AI policies.

5.3. Dominance of ChatGPT in Student AI Adoption

The strongest finding concerns the exceptionally high reported adoption of ChatGPT. In the present sample, 126 of 132 respondents (95.5%) report using ChatGPT for academic purposes. Google Gemini is reported by 43.2%, other AI tools by 34.1%, and Microsoft Copilot by 9.1%.

The predominance of ChatGPT is broadly consistent with recent higher-education research. Baig and Yadegaridehkordi (2024) ^[3], in a systematic review of 57 studies, found that ChatGPT applications in higher education have expanded across academic staff, students, researchers, and other users. Stohr *et al.* (2024) ^[20] similarly found broad awareness and use of ChatGPT among university students, while usage of other AI chatbots was comparatively limited. Jo (2024) ^[14] further describes AI chatbots as increasingly integrated into the digital learning environment and identifies behavioural determinants influencing student use of ChatGPT.

The present finding of 95.5% ChatGPT adoption is particularly pronounced. However, the result should not be interpreted as evidence that ChatGPT is universally preferred by university students or that it is academically superior to Gemini, Copilot, or other tools. The current study measures reported adoption, not effectiveness, satisfaction, accuracy, learning outcomes, or preference.

The multiple-response structure is also methodologically important. Because respondents could select more than one AI tool, the percentages represent the proportion of respondents reporting use of each tool and do not constitute mutually exclusive market shares. A student selecting ChatGPT, Gemini, and Copilot contributes to the adoption percentage of all three tools. Accordingly, the results demonstrate the breadth of exposure to different AI platforms rather than exclusive platform choice.

5.4. High Frequency of Academic AI Use

The frequency distribution provides further evidence of substantial AI engagement. Of the 132 respondents, 57 (43.2%) report using AI tools “Often” and 39 (29.5%) report using them “Very Often.” Thus, 96 respondents, representing 72.7% of the sample, report relatively frequent academic AI use.

This finding is consistent with the broader literature indicating that GenAI has moved beyond experimental

novelty toward regular use in higher education. Baig and Yadegaridehkordi (2024) ^[3] documented the diversification of ChatGPT applications across higher-education contexts, while Stohr *et al.* (2024) ^[20] found broad student awareness and regular use of AI chatbots. The Digital Education Council's Global AI Student Survey also indicates that AI use and institutional readiness have become significant concerns for university students internationally.

The high frequency observed in the present study may reflect the increasing accessibility and versatility of GenAI tools for activities such as brainstorming, explanation, drafting, summarisation, language support, and information exploration. However, the available data do not identify the specific purposes for which students use AI or whether frequent use is academically productive.

This distinction is critical. Frequency of AI use is not equivalent to learning effectiveness. Recent evidence suggests that GenAI can support learning when incorporated into appropriately designed educational activities, but outcomes vary according to the learner, tool, task, instructional role, and learning context. Chen and Cheung's (2025) ^[8] meta-analysis reported positive effects of GenAI on several university learning outcomes, while also identifying substantial contextual variation and no significant overall effect on metacognition.

Therefore, the 72.7% frequent-use rate observed in the present study should be interpreted as evidence of behavioural adoption, not as evidence of educational benefit.

5.5. AI Adoption Does Not Necessarily Imply Academic Improvement

An important contribution of the present analysis is the distinction between the prevalence of AI use and its educational consequences. The dataset does not contain academic grades, assignment-quality measures, learning-experience measures, productivity indicators, or validated measures of critical thinking. Consequently, no statistical relationship between AI use and academic performance can be established.

This limitation is especially important because recent empirical literature presents a generally positive but increasingly nuanced picture of GenAI-supported learning. Deng *et al.* (2025) ^[10], in a systematic review and meta-analysis of experimental studies, reported positive effects of ChatGPT interventions on academic performance, affective-motivational states, and higher-order thinking propensities. Chen and Cheung (2025) ^[8] similarly found positive effects of GenAI on academic achievement and higher-order thinking, although the effect on metacognition was not statistically significant. More recently, Mo *et al.* (2026) ^[16], synthesising 66 studies and 129 effect sizes, reported a large positive overall effect of ChatGPT applications on undergraduate learning outcomes.

These findings demonstrate why it would be inappropriate to infer academic effects from the present descriptive data alone. The literature increasingly supports the possibility that GenAI can enhance learning under appropriate conditions, but those conclusions are based on studies that include explicit outcome measures and, in many cases, experimental or quasi-experimental designs.

The present study instead establishes that AI tools are widely used among the surveyed students. It does not establish what students learn from that use, whether their grades improve, or

whether AI changes their academic productivity. This distinction strengthens the methodological credibility of the present study by preventing unsupported causal interpretation.

5.6. Course and Year-of-Study Concentration

The academic profile indicates that BBA students constitute 52.3% of the sample and third-year students account for 86.4%. This concentration has important implications for interpretation.

The predominance of BBA students means that the overall AI-use pattern may reflect the academic requirements, digital practices, and technology exposure of business-oriented students more strongly than those of students from other disciplines. Likewise, the concentration of third-year students means that the dataset cannot provide a balanced comparison of AI use across different stages of university education.

Recent literature confirms that disciplinary and academic-level characteristics can influence AI adoption and perceptions. Stohr *et al.* (2024) ^[20] found differences in AI-chatbot use and attitudes across academic fields and levels, while Baek *et al.* (2024) ^[2] reported that academic major was associated with patterns of ChatGPT use.

The present concentration therefore represents both a substantive characteristic and a sampling limitation. The marginal distributions for course and year of study cannot be combined with the overall frequency distribution to infer course-specific or year-specific usage patterns. Such comparisons require complete respondent-level cross-tabulations.

5.7. Implications for AI Literacy and Responsible Use

The high level of AI adoption observed in the study has important implications for higher-education institutions. Since 95.5% of respondents report using ChatGPT and 72.7% report frequent or very frequent AI use, AI literacy should be considered an integral component of contemporary higher education rather than an optional digital skill.

Recent research increasingly conceptualises AI literacy as more than the ability to operate an AI tool. Tzirides *et al.* (2024) ^[24] emphasise the development of AI literacy through interaction between human and AI systems, while Yan *et al.* (2025) ^[27] demonstrate that sustained engagement with GenAI can develop prompt-engineering skills, metacognitive awareness, critical evaluation of outputs, and ethical boundaries.

These findings suggest that institutions should move beyond simply teaching students how to generate AI outputs. Effective AI literacy should include the ability to formulate appropriate prompts, evaluate the reliability of AI-generated information, recognise hallucinations and bias, verify sources, protect personal and institutional data, acknowledge AI assistance where required, and retain human responsibility for academic decisions.

UNESCO's guidance similarly advocates a human-centred approach to GenAI in education, emphasising ethical, safe, equitable, meaningful, and pedagogically appropriate use.

The present study cannot determine whether respondents possess these competencies because AI-literacy measures were not included in the available dataset. Nevertheless, the high adoption rate provides a strong rationale for incorporating such competencies into future institutional research and educational practice.

5.8. Academic Integrity and Assessment Implications

The widespread use of AI also has implications for academic integrity and assessment design. Although the present dataset does not contain measures of academic-integrity concerns, the issue is important in interpreting the broader educational context of high AI adoption.

Gruenhagen *et al.* (2024) ^[13], surveying 337 Australian university students, found that more than one-third had used chatbots for assistance with assessments and that students did not necessarily regard such use as a breach of academic integrity. Their findings highlight the need for clearer institutional expectations concerning permissible AI assistance.

Similarly, Luo (2024) ^[15], examining GenAI policies at 20 leading universities, found that concerns about originality and students submitting work that does not adequately represent their independent intellectual contribution were central to institutional policy responses. The study also highlights concerns related to reliability and equitable access. These findings have relevance for the present study because the very high level of AI adoption suggests that traditional assumptions about completely AI-free academic work may no longer correspond to actual student behaviour. Rather than focusing exclusively on prohibition, institutions may need to distinguish between appropriate assistance and inappropriate substitution of AI for students' own intellectual work.

Assessment design may therefore need to place greater emphasis on process, application, reflection, oral defence, problem-solving, source verification, and demonstrable individual reasoning. However, such recommendations should be understood as implications from the wider literature rather than direct empirical findings from the present dataset.

5.9. Implications for Higher-Education Policy and Teaching Practice

The findings suggest that institutional responses to GenAI should focus on structured integration rather than treating AI use solely as a technological or disciplinary issue. The combination of very high ChatGPT adoption and frequent AI use indicates that students are already engaging with GenAI at substantial levels.

Recent research shows that institutional policy can influence student AI use. Baek *et al.* (2024) ^[2] found that institutional policy was associated with patterns of ChatGPT use, while Wang *et al.* (2024) ^[26] documented how universities are developing policies, resources, and guidelines in response to the opportunities and challenges created by GenAI.

For institutions such as KL University, this implies the value of transparent and discipline-sensitive AI-use guidelines. Such guidelines could specify when AI use is permitted, when disclosure is required, how AI-generated material should be verified, and which forms of assessment require independent student work.

Faculty development is equally important. Instructors need support not only in detecting inappropriate AI use but also in designing learning activities in which AI can be used constructively while preserving student agency. The emerging literature on AI literacy indicates that students benefit from opportunities to critically engage with AI rather than simply receiving unrestricted access to it (Tzirides *et al.*, 2024; Yan *et al.*, 2025) ^[24, 27].

5.10. Methodological Implications and Limitations

The present findings must be interpreted within the limitations of the research design. First, convenience sampling limits the representativeness of the sample. The 132 respondents cannot therefore be assumed to represent all students at KL University or students in other Indian higher-education institutions.

Second, the cross-sectional design captures AI-use behaviour at one point in time and cannot establish changes in usage patterns or causal relationships. This is particularly important when interpreting the literature on AI and academic outcomes because experimental studies and longitudinal research provide stronger evidence regarding educational effects than descriptive cross-sectional surveys.

Third, the sample is highly concentrated by age, course, and year of study. This restricts subgroup comparisons and limits generalisability. Fourth, the multiple-response nature of AI-tool adoption means that individual tool percentages cannot be interpreted as exclusive shares.

Finally, and most importantly, the academic-outcome variables proposed in the broader research framework are not available in the dataset. Thus, the study cannot test whether AI use is associated with academic performance, learning experience, assignment quality, productivity, or academic-integrity concerns. This limitation is particularly relevant because recent meta-analyses report potentially positive effects of GenAI on learning outcomes but emphasise contextual and methodological heterogeneity (Chen & Cheung, 2025; Deng *et al.*, 2025; Mo *et al.*, 2026) ^[8, 10, 16].

5.11. Directions for Future Research

Future research should extend the present descriptive framework by collecting matched measures of AI use and academic outcomes from the same respondents. AI use should be measured not only in terms of frequency but also by purpose, duration, task type, level of dependence, verification behaviour, and degree of human involvement.

Academic outcomes could include objective academic scores, assignment performance, learning gains, critical-thinking measures, or validated learning-experience scales. Such data would permit correlation, regression, structural equation modelling, or other appropriate inferential techniques.

Future studies should also retain item-level responses so that reliability and construct validity can be assessed for multi-item measures. Larger and more balanced samples should be obtained across gender, age, academic programme, and year of study. Stratified or probability-based sampling would improve representativeness.

Longitudinal and experimental designs would be particularly valuable. They could determine whether repeated AI use produces sustained improvements in learning or whether benefits depend on instructional design and the nature of the academic task. Recent meta-analytic evidence suggests that GenAI effects vary according to learner characteristics, tool use, instructional role, intervention duration, and contextual conditions (Chen & Cheung, 2025) ^[8].

Future studies should also examine AI literacy, academic integrity, verification practices, and students' perceptions of acceptable AI use. Yan *et al.* (2025) ^[27] indicate that sustained interaction with GenAI can support the development of more sophisticated AI literacy, including prompt engineering,

critical evaluation, metacognition, and ethical boundaries.

5.12. Overall Discussion

The present study demonstrates that AI tools have achieved substantial penetration into academic practices among the surveyed students at KL University, Vijayawada. ChatGPT is particularly dominant, with 95.5% of respondents reporting its use, while 72.7% report using AI tools often or very often. These findings are broadly consistent with recent international evidence documenting the rapid diffusion of GenAI within higher education (Baig & Yadegaridehkordi, 2024; Jo, 2024; Stohr *et al.*, 2024) ^[3, 14, 20].

The study also identifies a descriptive gender difference in AI-use frequency, although the evidence does not justify a claim of statistical significance. The finding differs from some recent European studies reporting higher male AI use, reinforcing the importance of institutional and cultural context when interpreting demographic patterns (Stohr *et al.*, 2024; Møgelvang *et al.*, 2024) ^[17, 20].

The wider literature increasingly suggests that GenAI can support student learning when embedded in appropriate pedagogical environments, with recent meta-analyses reporting positive effects on academic achievement and higher-order thinking (Chen & Cheung, 2025; Deng *et al.*, 2025; Mo *et al.*, 2026) ^[8, 10, 16]. Nevertheless, those findings cannot be transferred directly to the present dataset because academic-outcome measures were not collected or made available.

The principal contribution of the present study is therefore empirical documentation of AI adoption and usage behaviour, rather than measurement of AI's academic impact. The high adoption and frequency of use observed in the sample demonstrate the importance of institutional AI literacy, responsible-use guidance, transparent assessment policies, and continued empirical monitoring. Future research incorporating respondent-level AI-use and academic-outcome measures is necessary to establish whether the extensive adoption observed in this study translates into measurable educational benefits or unintended academic consequences.

6. Conclusion

This study examined AI-tool adoption and usage patterns among college students at KL University, Vijayawada, using 132 usable responses and a quantitative, descriptive, cross-sectional design. ChatGPT was the most widely used AI tool (95.5%), followed by Google Gemini (43.2%), other AI tools (34.1%), and Microsoft Copilot (9.1%). Overall, 72.7% of respondents reported using AI tools often or very often for academic purposes, indicating that AI has become a relatively regular component of academic activity within the surveyed sample. Descriptively, frequent AI use was higher among female respondents (80.0%) than male respondents (57.1%); however, this difference was not tested for statistical significance.

The findings primarily establish AI adoption and usage behaviour, rather than its academic impact. The available dataset does not contain the academic-performance and related outcome measures required to determine whether AI use improves or reduces academic outcomes. Therefore, no causal conclusions can be drawn from the observed usage patterns. The findings nevertheless highlight the need for higher-education institutions to strengthen AI literacy,

responsible use, information verification, academic integrity, and critical evaluation of AI-generated content.

The study is limited by convenience sampling, its cross-sectional design, a concentrated respondent profile, and the absence of academic-outcome variables. Future research should use larger and more diverse samples and integrate respondent-level AI-use measures with reliable academic-performance indicators, preferably through longitudinal or experimental designs. Overall, the study provides institution-specific evidence of widespread and relatively frequent AI adoption while establishing a basis for more rigorous investigation of its educational consequences.

References

1. Almasri F. Examining the effect of artificial intelligence in relation to students' academic achievement: A meta-analysis. *Computers and Education: Artificial Intelligence*. 2025;8:100400. doi:10.1016/j.caeai.2025.100400
2. Baek C, Tate T, Warschauer M. "ChatGPT seems too good to be true": College students' use and perceptions of generative AI. *Computers and Education: Artificial Intelligence*, 7, 100294. 2024. doi:10.1016/j.caeai.2024.100294
3. Baig MI, Yadegaridehkordi E. ChatGPT in higher education: A systematic literature review and research challenges. *International Journal of Educational Research*. 2024;127:102411. doi:10.1016/j.ijer.2024.102411
4. Bhullar PS, Joshi M, Chugh R. ChatGPT in higher education—A synthesis of the literature and a future research agenda. *Education and Information Technologies*. 2024;29:21501-21522. doi:10.1007/s10639-024-12723-x
5. Bonett DG, Wright TA. Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of Organizational Behavior*. 2015;36(1):3-15. doi:10.1002/job.1960
6. Castillo-Martínez IM, Ramírez-Montoya MS, others. Artificial intelligence in higher education: A systematic review of empirical studies and emerging research directions. *Education and Information Technologies*. 2024;29:1-30.
7. Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20, Article 43. <https://doi.org/10.1186/s41239-023-00411-8>
8. Chen S, Cheung ACK. Effect of generative artificial intelligence on university students' learning outcomes: A systematic review and meta-analysis. *Educational Research Review*; 2025. doi:10.1016/j.edurev.2025.100737
9. Creswell JW, Creswell JD. *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications; 2018.
10. Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education*, 227, 105224. <https://doi.org/10.1016/j.compedu.2024.105224>
11. Eke DO. ChatGPT and the rise of generative AI: Threat to academic integrity? *Journal of Academic Ethics*. 2023;21:1-5.

12. Essel HB, Vlachopoulos D, Essuman AB, Amankwa JO. ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education: Artificial Intelligence*. 2024;6:100198. doi:10.1016/j.caeai.2023.100198
13. Gruenhagen JH, Sinclair PM, Carroll JA, Baker PRA, Wilson A, Demant D. The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. *Computers and Education: Artificial Intelligence*. 2024;7:100273. doi:10.1016/j.caeai.2024.100273
14. Jo, H. (2024). From concerns to benefits: A comprehensive study of ChatGPT usage in education. *International Journal of Educational Technology in Higher Education*, 21, 35. <https://doi.org/10.1186/s41239-024-00471-4>
15. Luo J. A critical review of GenAI policies in higher education assessment: A call to reconsider the "originality" of students' work. *Assessment & Evaluation in Higher Education*. 2024;49(5):651-664. doi:10.1080/02602938.2024.2309963
16. Mo, F., Huang, J., Yang, Y., Özen, Z., Maeda, Y., & Olenchak, F. R. (2026). Undergraduate students' learning outcomes with ChatGPT: A meta-analytic study. *Computers and Education: Artificial Intelligence*, 10, 100536. <https://doi.org/10.1016/j.caeai.2025.100536>
17. Møgelvang A, Bjelland C, Grassini S, Ludvigsen K. Gender differences in the use of generative artificial intelligence chatbots in higher education: Characteristics and consequences. *Education Sciences*. 2024;14(12):1363. doi:10.3390/educsci14121363
18. Saunders M, Lewis P, Thornhill A. *Research methods for business students* (8th ed.). Pearson; 2019.
19. Sekaran U, Bougie R. *Research methods for business: A skill-building approach* (7th ed.). John Wiley & Sons; 2016.
20. Stohr, C., Ou, A. W., & Malmström, H. (2024). Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. *Computers and Education: Artificial Intelligence*, 7, 100259. <https://doi.org/10.1016/j.caeai.2024.100259>
21. Sun L, Zhou L. Generative artificial intelligence and learning: A systematic review of educational applications and outcomes. *Computers and Education: Artificial Intelligence*. 2024a;7:100262.
22. Sun L, Zhou L. Does generative artificial intelligence improve the academic achievement of college students? A meta-analysis. *Journal of Educational Computing Research*. 2024b;62(7):1672-1698. doi:10.1177/07356331241277937
23. Taber KS. The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*. 2018;48:1273-1296. doi:10.1007/s11165-016-9602-2
24. Tzirides AO, Zapata G, Kastania NP, Saini AK, Castro V, Ismael SA, et al. Combining human and artificial intelligence for enhanced AI literacy in higher education. *Computers and Education Open*. 2024;6:100184. doi:10.1016/j.caeo.2024.100184
25. UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO.
26. Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence*, 7, 100326. <https://doi.org/10.1016/j.caeai.2024.100326>
27. Yan W, Nakajima T, Sawada R. Beyond tool use: Tracking the evolution of generative AI literacy among university students through a process-oriented investigation. *Computers and Education: Artificial Intelligence*. 2025;9:100465. doi:10.1016/j.caeai.2025.100465
28. Yusuf A, Pervin N, Roman-Gonzalez M. Generative AI and the future of higher education: A systematic review of opportunities, challenges, and implications. *Education Sciences*. 2024;14(6):676.
29. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, 16, Article 39. <https://doi.org/10.1186/s41239-019-0171-0>

How to Cite This Article

Chandra Sekhar S, Golla A. Generative AI adoption and usage patterns among college students in Vijayawada, India. *Global Multidisciplinary Perspectives Journal*. 2026;3(5):38–49. doi:10.54660/GMPJ.2026.3.5.38-49.

Creative Commons (CC) License

This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution NonCommercial-ShareAlike 4.0 International (CC BYNC-SA 4.0) License, which allows others to remix, tweak, and build upon the work non-commercially, as long as appropriate credit is given and the new creations are licensed under the identical terms