Engineering and Technology Journal e-ISSN: 2456-3358

Volume 11 Issue 06 June-2026, Page No.- 10419-10435

DOI: 10.47191/etj/v11i06.18, I.F. – 8.595

AI Tool Usage and Academic Reliance: A Quantitative Analysis of Patterns, Perceptions, and Instructor Influence

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ABSTRACT: This study examined patterns of AI tool use and reliance among 425 college students, the perceived impact on academic performance, and the role of instructor guidance in shaping these behaviors. A descriptive-correlational research design was employed, utilizing a structured online questionnaire. Results indicated that the vast majority of respondents used AI tools several times a week (52%) or daily (34.4%), primarily to check grammar and spelling, generate ideas, and research topics. Most students (52.9% agree; 36.9% strongly agree) perceived AI tools as improving their learning experience, and 94.6% reported a positive impact on their academic performance. Spearman correlation analysis revealed a statistically significant positive relationship between instructor encouragement and AI usage frequency ($r_s = 0.1144$, $p < .05$), and between instructor encouragement and students' intention to continue using AI tools in the future ($r_s = 0.1609$, $p < .001$). However, no statistically significant relationship was found between students' belief that AI improves learning and their self-reported grades ($r_s = 0.0226$, $p > .05$). Additionally, the purpose of AI use (writing, research, math, grammar) did not significantly differentiate grade levels among students. The findings underscore the widespread integration of AI into students' academic routines and the influential role instructors play in mediating responsible AI adoption.

KEYWORDS: Artificial Intelligence, AI Tools, Academic Performance, Student Reliance, Instructor Guidance, Higher Education

INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technologies in education has fundamentally altered how students approach learning, research, and academic work. Tools such as ChatGPT, Grammarly, Turnitin, and Photomath have become embedded in the daily academic routines of higher education students worldwide. While proponents argue that these tools democratize access to information and enhance productivity, critics express concern about growing student dependency, diminishing critical thinking skills, and questions of academic integrity. This tension has placed educators at a crossroads seeking to harness the benefits of AI while mitigating its potential risks.

In the Philippine higher education context, where access to technology is expanding rapidly but digital literacy frameworks are still evolving, understanding how students interact with AI tools is both timely and essential. As institutions formulate policies on AI use, empirical evidence on student behavior, perceptions, and the mediating role of instructors is urgently needed. Without such evidence, policy decisions risk being either overly restrictive or insufficiently guided.

This study addresses this gap by examining the patterns of AI tool usage, students' perceived impact on academic performance, their self-assessed confidence and reliance, and the influence of instructor guidance on AI-related behaviors. The research focuses on the following objectives: (1) to determine the frequency, types, and purposes of AI tool usage among college students; (2) to assess students' self-reported reliance on and confidence without AI tools; (3) to evaluate the perceived impact of AI on learning and academic performance; (4) to examine the relationship between instructor encouragement or guidance and students' AI usage behaviors, risk awareness, and future use intentions; and (5) to investigate whether students' beliefs about AI's benefits and their purposes of use are associated with self-reported grades.

Research Questions

RQ1: Is there a significant relationship between instructors encouraging or discouraging AI use and the frequency with which students use these tools?

RQ2: Are students whose instructors have provided guidance on effective AI use more aware of the potential risks and limitations of these tools?

RQ3: How does instructor guidance or lack thereof correlate with students' intentions to use AI in their future academic or professional pursuits?

RQ4: Do students who believe AI is improving their learning experience report higher grades in their most challenging subject than students who are neutral or disagree?

RQ5: Is there a significant link between the purpose of AI use and the students' self-reported grade in their most challenging subject?

Review of Related Literature

AI in Higher Education

The integration of AI tools in academic settings has been the subject of growing scholarly interest. Research on educational technology adoption, grounded in the Technology Acceptance Model (TAM) proposed by Davis (1989), suggests that perceived usefulness and perceived ease of use are primary determinants of technology adoption. In the context of AI, students who perceive these tools as beneficial for productivity and learning quality are more likely to incorporate them into their academic routines. Recent studies have documented the widespread adoption of generative AI tools among university students globally, with usage rates exceeding 80% in many contexts, particularly for writing assistance, information retrieval, and problem-solving.

Student Reliance and Academic Self-Efficacy

Bandura's (1997) Social Cognitive Theory emphasizes the role of self-efficacy an individual's belief in their capacity to execute behaviors necessary to produce specific outcomes in shaping academic performance. The concern with AI tool reliance is that excessive dependence may erode students' confidence in performing academic tasks independently, thereby undermining self-efficacy. Several scholars have documented a paradox wherein AI tools simultaneously boost immediate productivity while potentially diminishing long-term skill development, particularly in writing, critical thinking, and mathematical reasoning.

Instructor Influence on AI Adoption

The role of instructors as gatekeepers and guides in technology-enhanced learning is well established. Drawing from Vygotsky's (1978) Zone of Proximal Development, instructors who provide structured guidance on AI tool use can help students navigate the boundary between productive tool-assisted learning and unhealthy dependency. Studies have shown that when educators actively model responsible AI use and integrate AI literacy into their pedagogy, students demonstrate more reflective and critical engagement with these technologies. Conversely, a lack of instructor guidance may leave students without a framework for evaluating AI outputs critically.

AI and Academic Performance

The relationship between AI tool use and academic performance remains contested in the literature. Some studies report modest positive associations, suggesting that AI tools help students organize their work, improve writing quality, and access information more efficiently. Others find no significant relationship, arguing that the tools serve as supplements rather than determinants of academic success. The inconsistency in findings may be attributable to differences in measurement approaches, particularly the reliance on self-reported grades and the heterogeneity of AI tools and use contexts. This study contributes to this body of evidence by examining the specific conditions under which AI use may or may not correlate with academic outcomes.

Theoretical Framework

This study is anchored on three theoretical foundations. First, the Technology Acceptance Model (TAM) by Davis (1989) provides the lens for understanding students' adoption patterns and perceived usefulness of AI tools. Second, Bandura's (1997) Self-Efficacy Theory offers a framework for examining students' confidence in performing academic tasks without AI assistance and their self-assessed reliance. Third, Vygotsky's (1978) Sociocultural Theory, particularly the concept of scaffolding, informs the analysis of instructor guidance as a mediating factor in students' AI behaviors and risk awareness

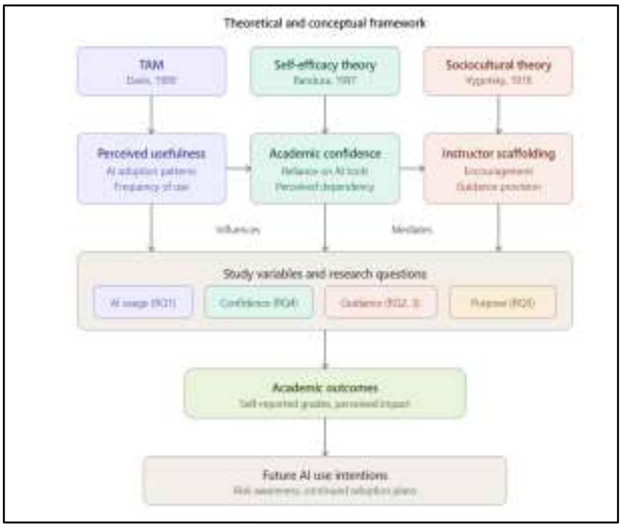

Fig. 1. Theoretical Framework

METHODOLOGY

Research Design

This study employed a quantitative, descriptive-correlational research design. The descriptive component characterized the patterns, perceptions, and self-reported behaviors of students regarding AI tool usage. The correlational component examined relationships among instructor-related variables (*encouragement, guidance*), student behaviors (*AI usage frequency, future use intentions*), perceptions (*risk awareness, perceived impact*), and academic outcomes (*self-reported grades*).

Respondents

The study involved 425 college students enrolled in a higher education institution in the Philippines. Respondents were predominantly aged 19–21 years ($M = 20.48$, $SD = 1.5$), with the majority in their 3rd year (56.5%) and 2nd year (33.6%) of study. Students represented diverse programs including Medical Technology, Pharmacy, Dentistry, Information Technology, and Computer Science. Convenience sampling was employed, with respondents recruited through their enrolled course sections.

Research Instrument

Data were collected through a structured online questionnaire titled "AI Tool Usage and Reliance Questionnaire." The instrument consisted of 20 items organized into five sections: (1) demographic information (2) AI usage patterns; (3) reliance and confidence (4) perceived impact on learning and grades; and (5) instructor role and future intentions Response formats included Likert-type scales (5-point), multiple-choice items, and select-all-that-apply checkboxes.

Data Collection

The questionnaire was administered electronically via Google Forms during the academic term. Participation was voluntary, and respondents were informed of the study's purpose and their right to withdraw at any time. No personally identifiable information was used in the analysis; email addresses and names were collected solely for verification of enrollment and were excluded from all statistical procedures.

Data Analysis

Descriptive statistics (*frequencies, percentages, means, and standard deviations*) were used to summarize respondent demographics, AI usage patterns, reliance, confidence, and perceptions. For inferential analysis, *Spearman's rank-order correlation* was applied to examine relationships between ordinal variables like instructor encouragement and AI frequency; instructor encouragement and future use intention. The *chi-square test* of independence was used to assess the association between instructor guidance and risk awareness, and between instructor guidance and future use. The *Kruskal-Wallis H test* was employed to compare self-reported grade distributions across groups of students with differing beliefs about AI's learning benefits. *Mann-Whitney U tests* were used to compare grades between students who used AI for a specific purpose versus those who did not. A significance level of $\alpha = .05$ was adopted for all inferential tests. All analyses were conducted using Python.

RESULTS AND DISCUSSION

Demographic Profile of Respondents

Table 1 presents the demographic profile of the 425 respondents. The largest group consisted of 3rd-year students (n = 240, 56.5%), followed by 2nd-year students (n = 143, 33.6%). Fourth-year and first-year students comprised smaller proportions of the sample. The mean age of respondents was 20.48 years (SD = 1.5), consistent with a sample of undergraduate students in their second and third years of college. The concentration of respondents in health sciences programs (Medical Technology, Pharmacy, Dentistry) reflects the institutional profile of the study site.

Table 1. Demographic Profile of Respondents (N = 425)

Year Level	Frequency (f)	Percentage (%)
1st Year	5	1.2%
2nd Year	143	33.6%
3rd Year	240	56.5%
4th Year	37	8.7%

Note. Mean age = 20.48 years (SD = 1.5).

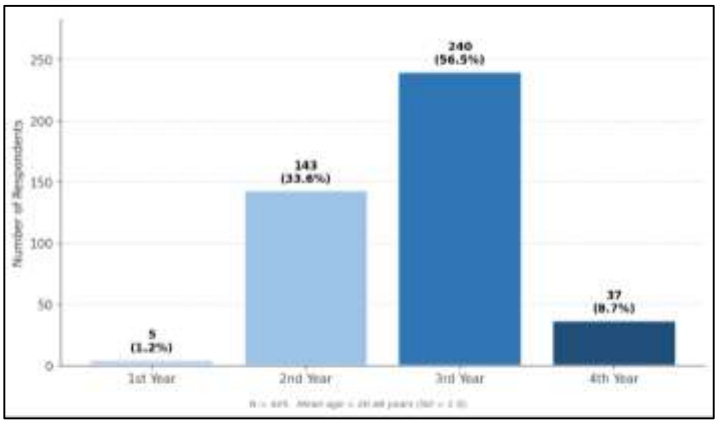

Fig. 2. Demographic Profile

As shown in Table 2, the majority of respondents reported using AI-powered tools several times a week (52%) or daily (34.4%). Only a negligible proportion reported rare usage (0.7%). The overall mean of 3.2 (SD = 0.68) on a 4-point scale indicates that AI tool usage is deeply embedded in the academic routines of these students. This finding aligns with the global trend documented in recent educational technology literature, which consistently reports high adoption rates of generative AI tools among university students (Chan & Hu, 2023; Crompton & Burke, 2023). The near-ubiquity of AI usage in this sample suggests that the question is no longer whether students use AI, but how and to what effect. Recent surveys across multiple countries confirm that the majority of college students engage with AI-powered tools on a near-daily basis, with generative AI platforms such as ChatGPT rapidly becoming embedded in academic workflows (Kasneci et al., 2023; Lo, 2023).

Table 2. Frequency of AI-Powered Tool Usage for Schoolwork

Frequency	f	%
Daily	146	34.4%
Several times a week	221	52%
Occasionally	55	12.9%
Rarely	3	0.7%

Note. Ordinal scale: Rarely = 1, Occasionally = 2, Several times a week = 3, Daily = 4. M = 3.2, SD = 0.68.

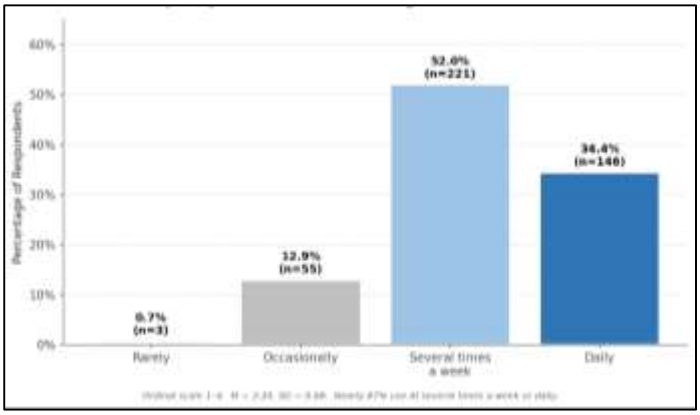

Fig. 3. AI-Powered Tool Usage for Schoolwork

Table 3 reveals that grammar and spell checkers (e.g., Grammarly) were the most commonly used AI tools (88%), followed by plagiarism detectors such as Turnitin (66.8%) and AI-powered writing assistants (50.6%). Virtual calculators and math solvers were less frequently reported (15.3%). This pattern indicates that students predominantly leverage AI for language and writing-related tasks, which is consistent with the academic demands of the programs represented in the sample. The dominance of grammar-checking tools corroborates findings by Karyuatry and Rizqan (2018), who demonstrated that automated proofreading platforms significantly improve the surface-level quality of student writing outputs. The high prevalence of plagiarism detection tool usage further reflects growing institutional pressure to uphold academic integrity in AI-augmented academic environments (Perkins, 2023; Cotton et al., 2024). The substantial uptake of AI writing assistants is consistent with recent surveys reporting that over half of university students in various global contexts employ generative AI for composing or refining academic texts (Tlili et al., 2023).

Table 3. AI-Powered Tools Most Frequently Used (Multiple Responses)

AI Tool	**f**	**%**
Grammar and spell checkers	374	88%
Plagiarism detectors	284	66.8%
AI-powered writing assistants	215	50.6%
Virtual calculators or math solvers	65	15.3%
Other	77	18.1%

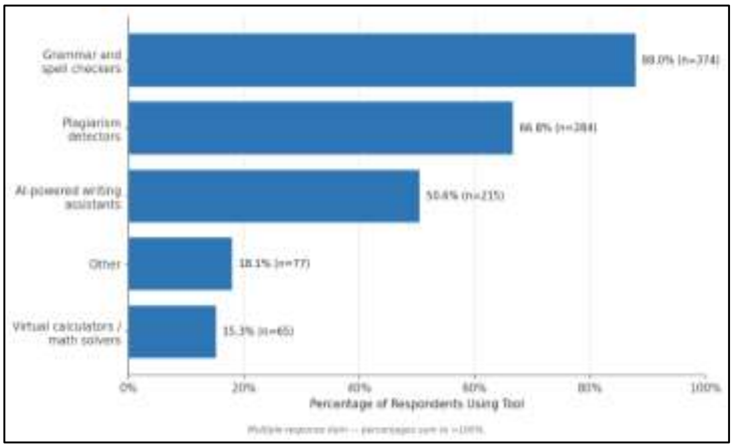

Fig. 4. AI-Powered Tools Most Frequently Used (Multiple Responses)

Table 4 shows that writing and editing papers (85.4%), checking grammar and spelling (80.7%), and researching topics (70.4%) were the top purposes for AI use. Solving math or science problems was cited by a smaller proportion (29.4%), likely reflecting the disciplinary composition of the sample, which was dominated by health sciences and language-intensive programs. These findings are corroborated by studies demonstrating that generative AI is predominantly employed for text-production and information-retrieval tasks in academic settings (Lo, 2023; Kasneci et al., 2023). The relatively lower use for mathematical problem-solving aligns with discipline-specific patterns identified by Lim et al. (2023), who noted that AI adoption is most intensive in humanities and social science contexts where written output is the primary deliverable.

Table 4. Purposes of AI Tool Usage (Multiple Responses)

Purpose	f	%
Writing and editing papers	363	85.4%
Checking grammar and spelling	343	80.7%
Researching topics	299	70.4%
Solving math or science problems	125	29.4%
Other	46	10.8%

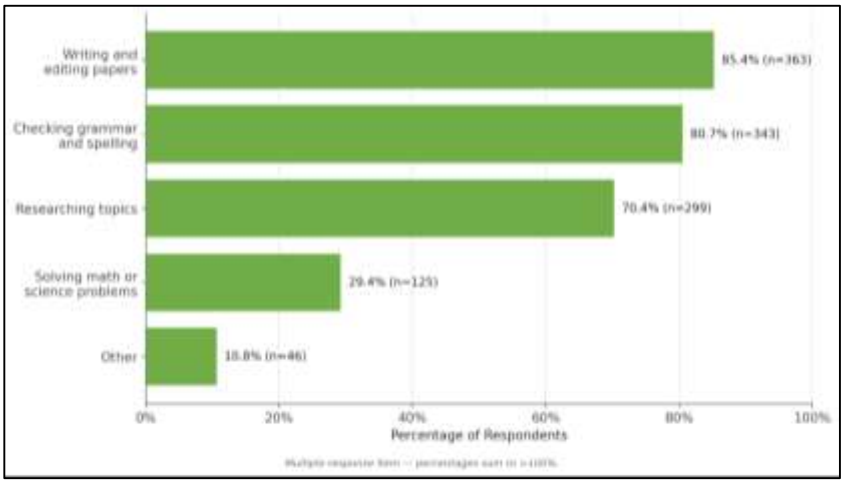

Fig. 5. Purposes of AI Tool Usage (Multiple Responses)

Table 5 summarizes the frequency of reliance on AI tools across five academic tasks. Students reported the highest reliance for checking grammar and spelling (M = 4.12, SD = 0.89) and writing or editing text (M = 3.75, SD = 0.91). Reliance was moderate for generating ideas (M = 3.79) and researching topics (M = 3.85). The lowest reliance was observed for solving math and science problems (M = 3.12, SD = 1), which is consistent with the predominantly non-quantitative nature of the respondents' programs. The elevated reliance on grammar-checking AI corroborates findings by Karyuatry and Rizqan (2018), who documented that automated proofreading tools are among the most consistently used AI applications in student academic workflows. The moderate-to-high reliance on idea generation and research further aligns with studies showing that AI is increasingly used as a cognitive scaffolding tool rather than merely a corrective one (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019).

Table 5. Frequency of Reliance on AI Tools by Task

Task	Mean	SD
Generate Ideas	3.79	0.81
Check Grammar	4.12	0.89
Research Topics	3.85	0.87
Solve Math/Science	3.12	1
Write/Edit Text	3.75	0.91

Note. Scale: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always.

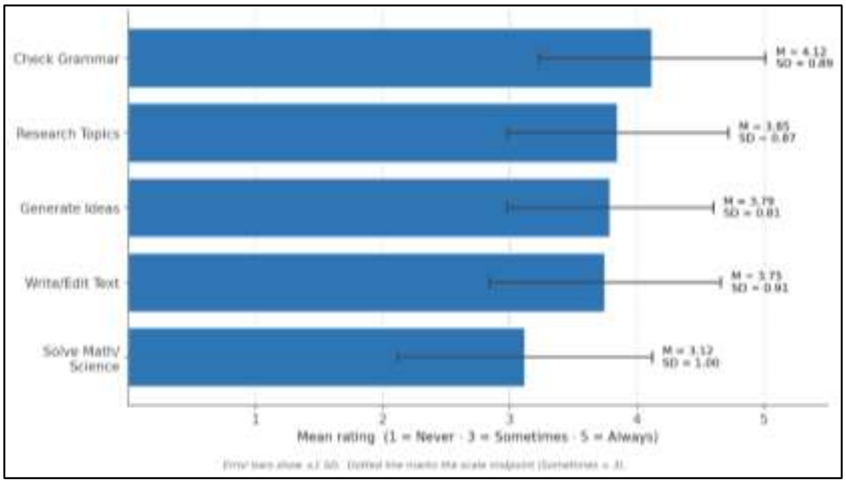

Fig. 6. Frequency of Reliance on AI Tools by Task

As presented in Table 6, students reported the highest confidence in their ability to write a well-structured essay without AI assistance (M = 3.94, SD = 0.64) and in researching credible sources independently (M = 3.84, SD = 0.91). Confidence in solving math problems without a calculator was notably lower (M = 3.39, SD = 1.01), suggesting that quantitative tasks pose a greater self-efficacy challenge (Bandura, 1997). The moderate-to-positive confidence levels across all domains suggest that while students use AI extensively, they have not entirely lost confidence in their independent abilities—though the gap between confidence in writing versus math warrants attention. These findings echo self-efficacy literature suggesting that academic confidence is domain-specific and can be differentially affected by sustained reliance on external technological supports (Zimmerman, 2000; Bandura, 1997).

Table 6. Self-Assessed Confidence in Performing Tasks Without AI

Academic Task	Mean	SD
Essay Writing	3.94	0.64
Math Problems	3.39	1.01
Research Skills	3.84	0.91

Note. Scale: 1 = Very unconfident, 2 = Slightly unconfident, 3 = Neutral, 4 = Somewhat confident, 5 = Very confident.

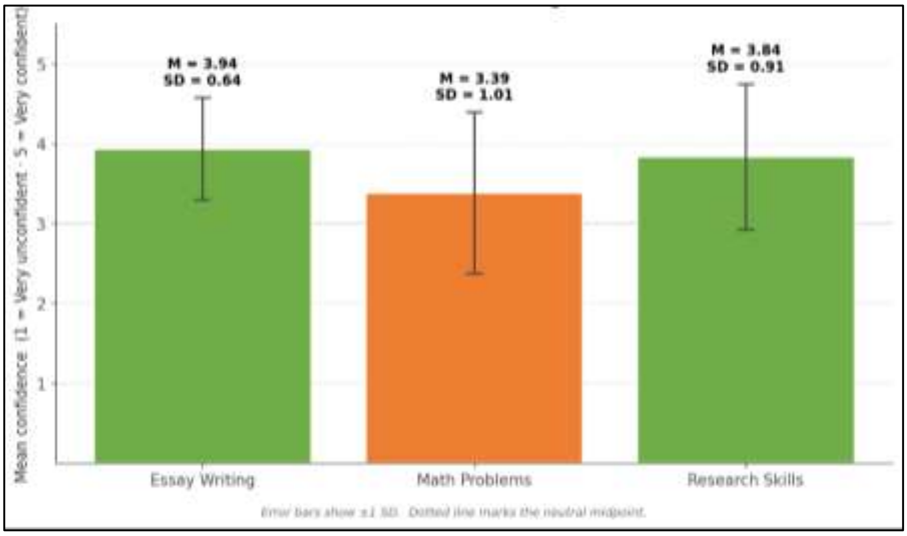

Fig. 7. Self-Assessed Confidence in Performing Tasks Without AI

Table 7 shows that the largest group of respondents (46.4%) took a neutral stance on whether they could not complete assignments without AI tools. Among those with a clear position, more students disagreed (28.2%) or strongly disagreed (6.1%) than agreed (16.2%) or strongly agreed (3.1%). The mean of 2.82 (below the scale midpoint of 3.0) suggests that, on the whole, students do not perceive themselves as unable to work without AI. However, the significant positive correlation between AI usage frequency and perceived dependency (r_s = 0.2876, $p < .001$) indicates that heavier users are more inclined to acknowledge dependency—a finding with important implications for academic self-efficacy (Bandura, 1997; Zimmerman, 2000). Research on technology dependency further suggests that habitual reliance on external tools can progressively attenuate intrinsic motivation and autonomous task engagement, especially when such reliance is reinforced across multiple academic contexts (Ouyang & Jiao, 2021).

Table 7. Perceived Inability to Complete Assignments Without AI Tools

Response	**f**	**%**
Strongly agree	13	3.1%
Agree	69	16.2%
Neutral	197	46.4%
Disagree	120	28.2%
Strongly disagree	26	6.1%

Note. M = 2.82, SD = 0.88. Scale: 1 = Strongly disagree to 5 = Strongly agree.

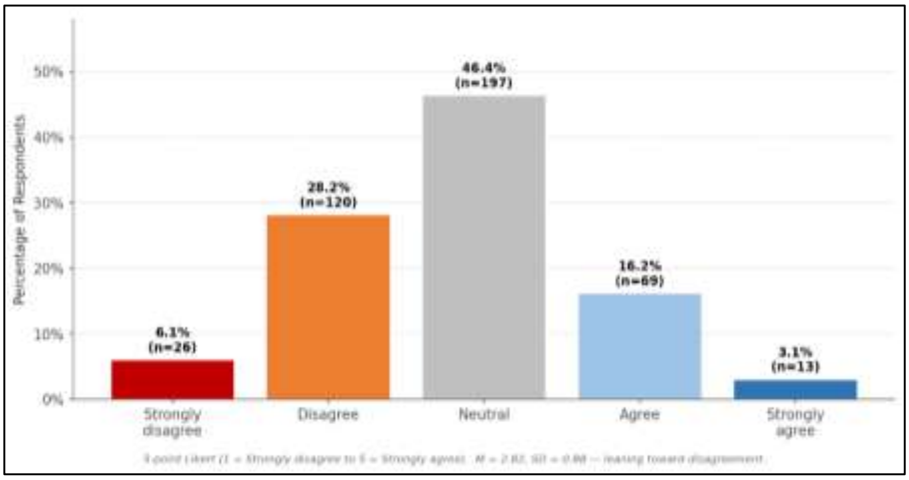

Fig. 8. *Self-Assessed Confidence in Performing Tasks Without AI*

An overwhelming majority of respondents agreed (52.9%) or strongly agreed (36.9%) that AI tools improve their learning experience (Table 8). Only 0.9% disagreed. The high mean score of 4.26 (SD = 0.66) reflects a strongly positive sentiment toward AI as a learning enhancer. This finding is consistent with the Technology Acceptance Model, which predicts that perceived usefulness is a primary driver of continued adoption.

Table 8. Students' Perception of AI Tools Improving Their Learning Experience

Response	f	%
Strongly agree	157	36.9%
Agree	225	52.9%
Neutral	39	9.2%
Disagree	4	0.9%

Note. M = 4.26, SD = 0.66.

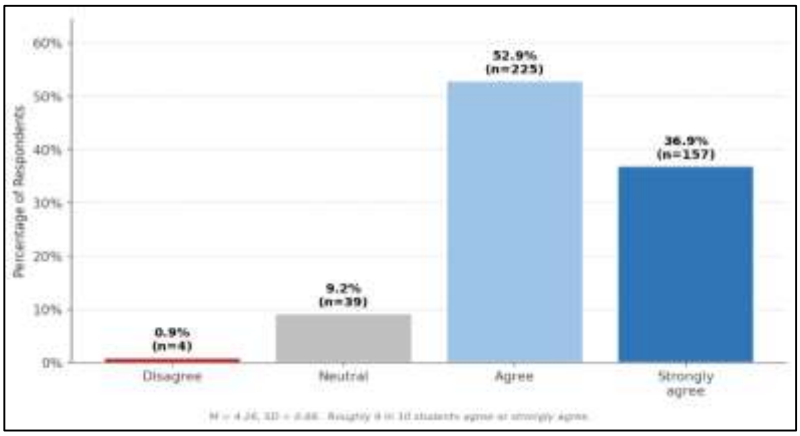

Fig. 9. Students' Perception of AI Tools Improving Their Learning Experience

Consistent with the preceding finding, Table 9 reveals that 72.5% of students perceived AI as positively impacting their academic performance, while an additional 22.1% rated the impact as very positive. Negative perceptions were exceedingly rare (0.7%). These findings collectively paint a picture of students who are enthusiastic about AI's role in their education—a narrative that educational institutions must engage with carefully. This aligns with studies noting that students' enthusiasm for AI-assisted learning frequently outpaces institutional frameworks for regulating its use (Lim et al., 2023; Cotton et al., 2024). Tlili et al. (2023) similarly reported that while student satisfaction with AI tools is consistently high, critical evaluation of AI output quality remains underdeveloped, pointing to a need for structured AI literacy integration in curricula.

Table 9. Perceived Impact of AI Tools on Academic Performance

Response	f	%
Very positively	94	22.1%
Positively	308	72.5%
No impact	20	4.7%
Negatively	3	0.7%

Note. M = 4.16, SD = 0.52. Scale: 1 = Very negatively to 5 = Very positively.

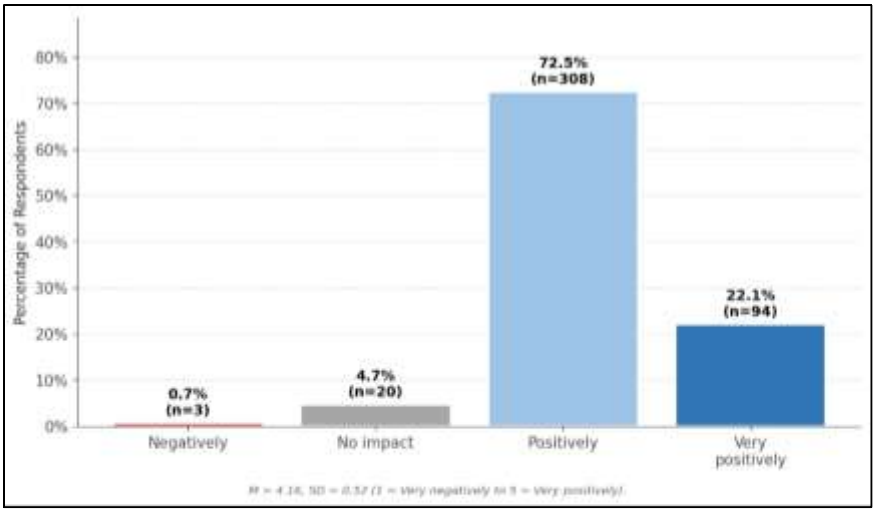

Fig. 10. Perceived Impact of AI Tools on Academic Performance

The majority of students (62.1%) reported grades in the 80–89% range in their most challenging subject, indicating generally satisfactory academic performance (Table 10). Students earning high marks (90–100%) constituted 16.7%, while those in the 70–79% bracket comprised 17.9%. This grade distribution is broadly consistent with academic performance benchmarks reported in higher education research examining AI-integrating student populations (Huang et al., 2021; Crompton & Burke, 2023), suggesting that widespread AI tool adoption does not markedly disrupt nor substantially elevate aggregate achievement distributions at the institutional level.

Table 10. Self-Reported Grades in Most Challenging Subject

Grade Range	f	%
1-1.75 (90–100%)	71	16.7%
2 -2.75(80–89%)	264	62.1%
3-3.5 (70–79%)	76	17.9%
4 (60–69%)	13	3.1%
5 (Below 60%)	1	0.2%

Note. M = 3.92, SD = 0.7. Higher values indicate better grades on the recoded scale.

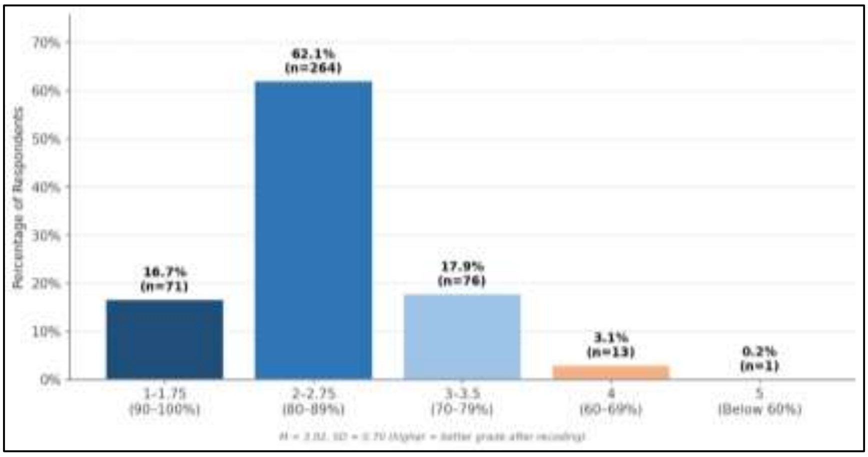

Fig. 11. Self-Reported Grades in Most Challenging Subject

Table 11 shows that instructors were generally perceived as encouraging (43.3%) or neutral (41.6%) toward AI use. Explicit discouragement was rare (discourage: 4.2%; strongly discourage: 1.2%). A substantial majority reported that their instructors had provided guidance on effective AI use (Yes: 89.9%). Similarly, most students indicated they would continue using AI in future academic or professional pursuits (Yes: 87.1%), and awareness of AI risks and limitations was nearly universal (Yes: 98.6%). These figures indicate a broadly permissive institutional climate for AI adoption, consistent with research showing that faculty attitudes and pedagogical choices significantly mediate students' technology integration behaviors (Mishra & Koehler, 2006; Selwyn, 2019). The high rate of instructor guidance provision further reflects growing institutional responsiveness to the need for structured AI literacy frameworks in higher education (Crompton & Burke, 2023).

Table 11. Instructor Encouragement or Discouragement of AI Tool Use

Response	f	%
Strongly encourage	41	9.6%
Encourage	184	43.3%
Neutral	177	41.6%
Discourage	18	4.2%
Strongly discourage	5	1.2%

Note. M = 3.56, SD = 0.77.

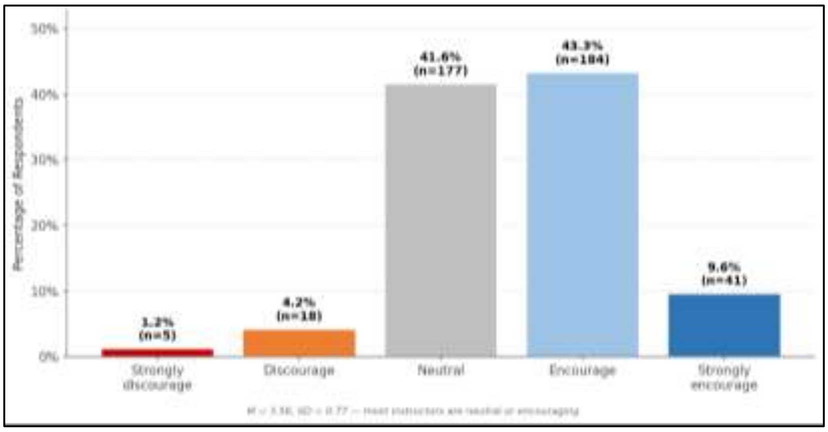

Fig. 12. Instructor Encouragement or Discouragement of AI Tool Use

Inferential Analyses

RQ1: Relationship Between Instructor Encouragement and AI Usage Frequency.

Spearman's rank correlation revealed a statistically significant, albeit weak, positive relationship between instructor encouragement and AI usage frequency ($r_s = 0.1144$, $p = .018$). This suggests that students whose instructors actively encourage AI use tend to employ these tools more frequently. While the effect size is small, the finding is practically meaningful: it indicates that instructor attitudes function as a contextual cue that shapes student behavior, consistent with sociocultural learning theories that emphasize the role of the instructor as a scaffold in technology-mediated learning environments (Vygotsky, 1978; Mishra & Koehler, 2006). These results extend prior work by Selwyn (2019), who argued that educators occupy a critical gatekeeping role in determining the pace and nature of technology adoption within academic communities.

Table 12. Spearman Correlation: Instructor Encouragement and AI Usage Frequency

Variables	n	r_s	p-value	Interpretation
Instructor Encouragement × AI Frequency	425	0.1144	0.018312	Significant

Note. Significance level: α = .05.

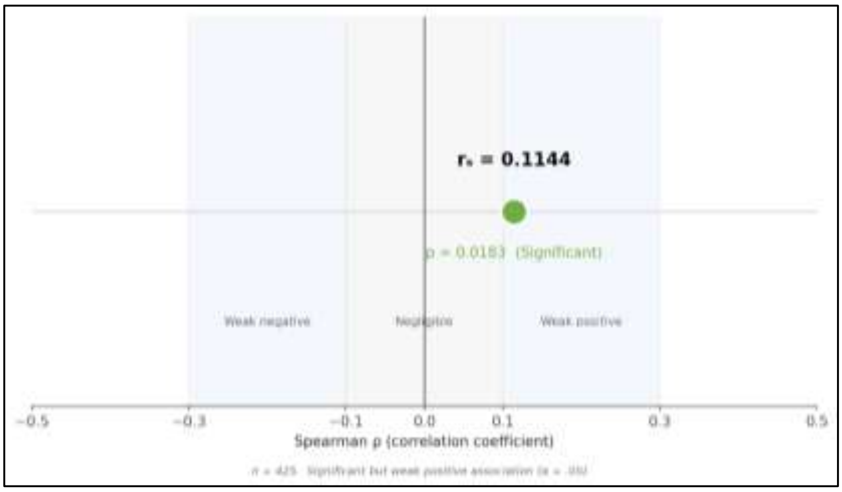

Fig. 13. Instructor Encouragement and AI Usage Frequency

The chi-square test of independence indicated no statistically significant association between instructor guidance and students' awareness of AI risks and limitations ($\chi^2 = 5.0731$, df = 2, p = .079). While the p-value approaches significance, it does not cross the conventional threshold. This may be partially attributable to a ceiling effect: an overwhelming 98.6% of all respondents reported being aware of AI risks regardless of whether their instructors had provided guidance. This near-universal awareness suggests that students may acquire risk knowledge from multiple sourcespeer discourse, media, or personal experiencenot solely from instructors

RQ2: Association Between Instructor Guidance and Risk Awareness.

The chi-square test of independence indicated no statistically significant association between instructor guidance and students' awareness of AI risks and limitations ($\chi^2 = 5.0731$, df = 2, p = .079). While the p-value approaches significance, it does not cross the conventional threshold. This may be partially attributable to a ceiling effect: an overwhelming 98.6% of all respondents reported being aware of AI risks regardless of whether their instructors had provided guidance. This near-universal awareness suggests that students may acquire risk knowledge from multiple sources—peer discourse, media, or personal experience—not solely from instructors. This pattern is consistent with research indicating that digital natives develop AI risk awareness through informal peer networks, social media, and personal experimentation rather than formal instruction alone (Perkins, 2023; Lo, 2023). Chan and Hu (2023) similarly found that students' self-reported understanding of AI limitations was high across institutional contexts, regardless of whether formal AI training was embedded in their programs.

Table 13. Chi-Square Test: Instructor Guidance and Risk Awareness

Test	χ^2	df	p-value	Interpretation
Guidance × Risk Awareness	5.0731	2	0.07914	Not Significant

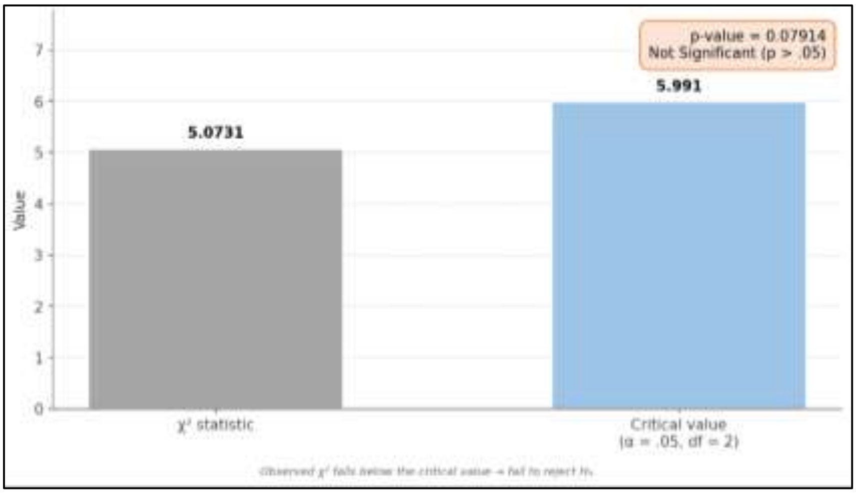

Fig. 14. Instructor Guidance and Risk Awareness

RQ3: Instructor Influence on Future AI Use Intentions.

Two analyses were conducted for this research question. The chi-square test for instructor guidance (yes/no) and future use intention was not statistically significant ($\chi^2 = 1.6727$, $p = .433$), suggesting that the mere provision of guidance does not predict whether students intend to continue using AI tools. However, Spearman's correlation revealed a statistically significant positive relationship between the degree of instructor encouragement and students' future use intentions ($r_s = 0.1609$, $p < .001$). This finding indicates that the nature and strength of instructor endorsement not simply whether guidance was offered plays a meaningful role in shaping students' long-term technology adoption plans. This is consistent with the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003), which identifies social influence including instructor endorsement as a key antecedent of sustained technology use intention. Mishra and Koehler (2006) similarly demonstrated that teacher facilitation behaviors shape students' technology integration intentions well beyond the classroom context.

Table 14. Correlation and Chi-Square: Instructor Factors and Future AI Use

Test	Statistic	Value	p-value	Interpretation
Guidance × Future Use (Chi-Square)	χ^2	1.6727	0.43329	Not Significant
Encouragement × Future Use (Spearman)	r_s	0.1609	< .001	Significant

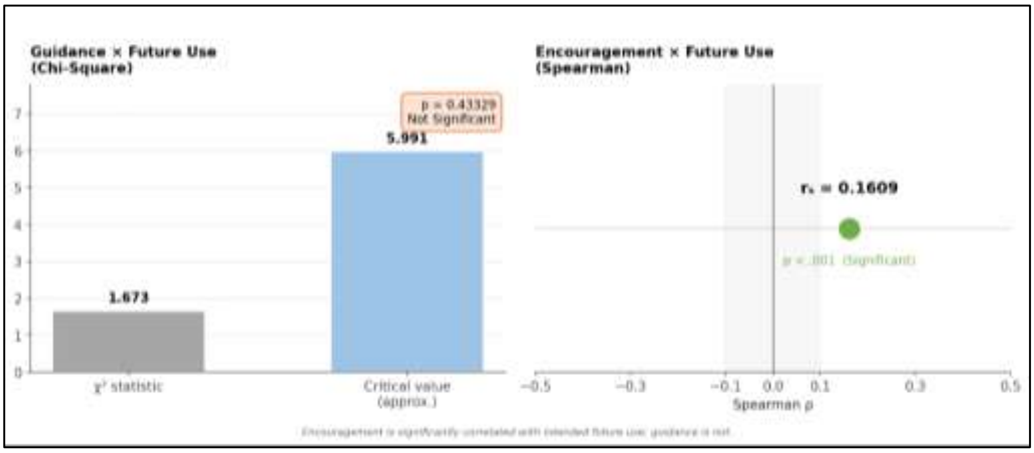

Fig. 15. Instructor Factors and Future AI Use

RQ4: Belief in AI's Learning Benefits and Self-Reported Grades.

The Kruskal-Wallis H test revealed no statistically significant difference in self-reported grades among students grouped by their belief about AI's impact on learning ($H = 1.4151$, $p = .493$). The Spearman correlation between the AI-improving perception and grade was similarly non-significant ($r_s = 0.0226$, $p = .642$). Students who agreed, were neutral, or disagreed that AI improves learning reported comparable grades. This null finding is noteworthy: it suggests that while students overwhelmingly believe AI enhances their learning, this belief does not translate into measurably higher (or lower) academic outcomes as captured by self-reported grades. The lack of association may reflect that grades are influenced by a complex array of factors study habits, prior knowledge, course difficulty that AI tools alone cannot override. This finding aligns with broader evidence in the educational AI literature indicating that perceived usefulness of AI does not reliably translate into improved objective performance metrics (Kasneci et al., 2023; Zhai et al., 2021). Crompton and Burke (2023) similarly concluded in their systematic review that the relationship between AI tool use and academic achievement is moderated by contextual and individual factors that attenuate simple bivariate associations.

Table 15. Kruskal-Wallis Test: AI Improving Belief Groups and Grades

Group	n	Mean Grade	SD
Agree	382	3.93	0.7
Disagree	4	4	0.82
Neutral	39	3.79	0.7
		H = 1.4151	p = 0.492838

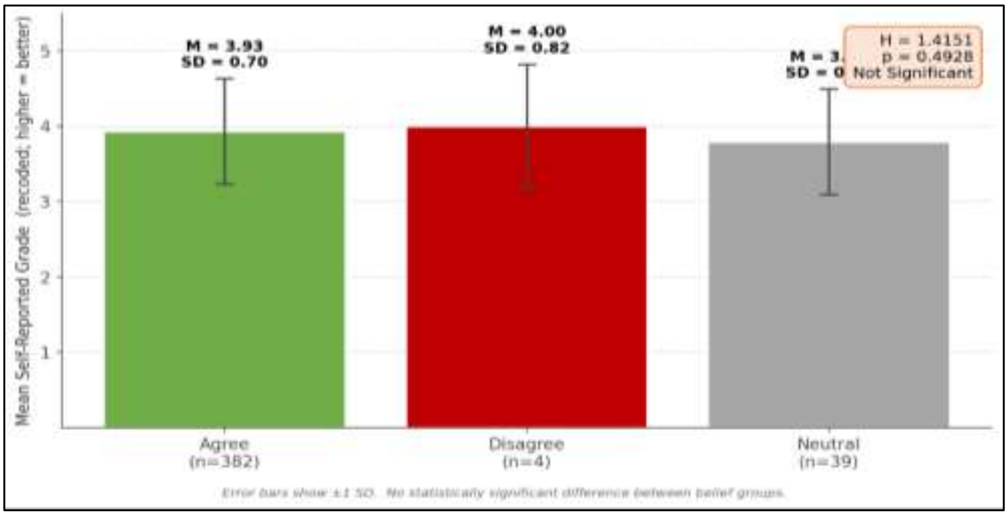

Fig. 16. AI Improving Belief Groups and Grades

RQ5: Purpose of AI

Mann-Whitney U tests were conducted to compare self-reported grades between students who used AI for each specific purpose versus those who did not. None of the four comparisons yielded statistically significant differences (all $p > .05$). Whether students used AI for writing, researching, solving math problems, or checking grammar, their grade distributions did not differ meaningfully from those who did not use AI for those purposes. This reinforces the conclusion from RQ4: AI tool usage, regardless of its specific application, does not appear to be a direct predictor of academic grades. This finding challenges the assumption that using AI for certain tasks (e.g., research or problem-solving) may confer a particular academic advantage. These results are consistent with systematic reviews finding limited direct effects of AI tool use on academic outcomes when confounding variables are uncontrolled (Zawacki-Richter et al., 2019; Crompton & Burke, 2023). Zhai et al. (2021), reviewing a decade of AI in education research, similarly concluded that the mediation of contextual and motivational variables frequently accounts for the absence of direct AI-performance linkages in cross-sectional designs.

Table 16. Mann-Whitney U Tests: Purpose of AI Use and Grades

Purpose	Users (n, M)	Non-Users (n, M)	U	p	Result
Writing/Editing	363 (M=3.9)	62 (M=4.02)	10273	0.2057	Not Sig.
Researching	299 (M=3.93)	126 (M=3.89)	19575.5	0.4612	Not Sig.
Math/Science	125 (M=3.87)	300 (M=3.94)	18051	0.4845	Not Sig.
Grammar	343 (M=3.91)	82 (M=3.98)	13405.5	0.4477	Not Sig.

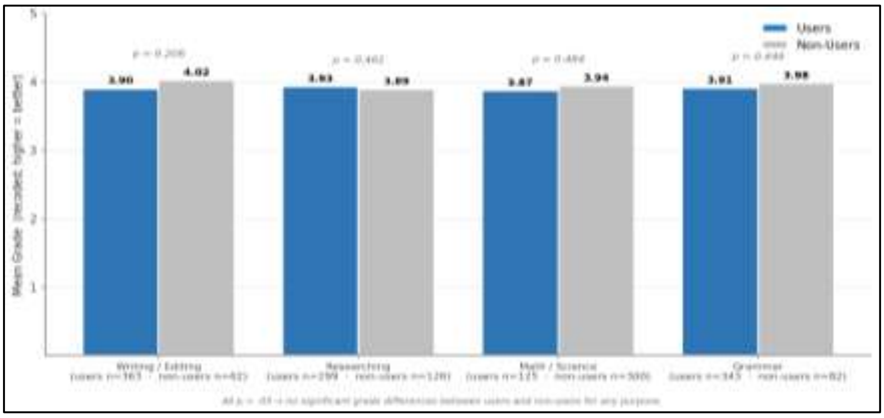

Fig. 17. Purpose of AI Use and Grades

Table 17 presents supplementary Spearman correlations among key study variables. Several noteworthy patterns emerged. First, AI usage frequency was significantly and positively correlated with perceived impact on performance (r_s = 0.2064, $p < .001$), perceived dependency (r_s = 0.2876, $p < .001$), and belief that AI improves learning (r_s = 0.1963, $p < .001$). These associations suggest a self-reinforcing cycle: students who use AI more frequently perceive greater benefits, which in turn may sustain or increase usage (Davis, 1989; Chan & Hu, 2023). Second, perceived dependency was negatively correlated with confidence in essay writing (r_s = -0.2262, $p < .001$), indicating that students who feel unable to complete assignments without AI also report lower confidence in their independent writing abilities. This aligns with self-efficacy theory, which predicts that overreliance on external supports may erode intrinsic confidence (Bandura, 1997; Zimmerman, 2000). Third, instructor encouragement was significantly associated with students' perception that AI improves learning (r_s = 0.2665, $p < .001$), further highlighting the instructor's role in shaping student attitudes. This triangulation of results underscores the complex interplay between cognitive self-regulation, technology use, and social learning mediated by instructor influence (Vygotsky, 1978; Mishra & Koehler, 2006).

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Table 17. Summary of Key Spearman Correlations

Variable Pair	n	r_s	p-value	Interpretation
AI Freq vs Impact	425	0.2064	< .001	Significant
AI Freq vs Grade	425	0.0158	0.745869	Not Significant
AI Improving vs Grade	425	0.0226	0.642324	Not Significant
Dependency vs Essay Conf	425	-0.2262	< .001	Significant
Dependency vs Grade	425	-0.0927	0.056318	Not Significant
Encourage vs AI Improving	425	0.2665	< .001	Significant
Impact vs Grade	425	0.0495	0.308446	Not Significant
AI Freq vs Dependency	425	0.2876	< .001	Significant
AI Freq vs Improving	425	0.1963	< .001	Significant

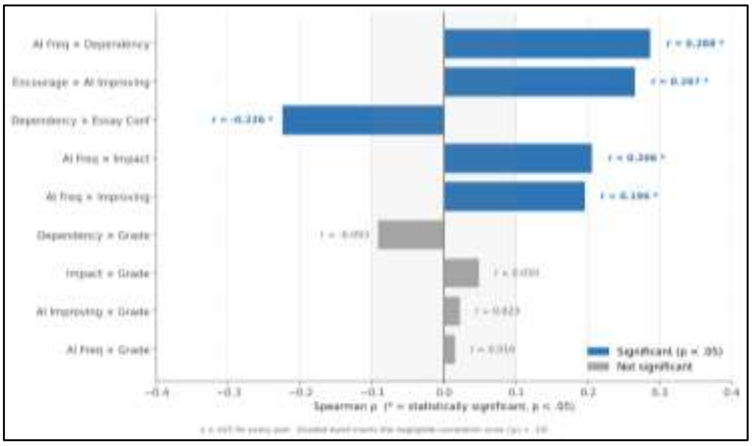

Fig. 18. Summary of Key Spearman Correlations

CONCLUSION

This study provides empirical evidence on the widespread adoption of AI tools among 425 college students and their perceptions of these tools' impact on learning and academic performance. The findings lead to the following conclusions: 1. First, AI tool usage is pervasive and deeply integrated into students' academic routines. The overwhelming majority of respondents use AI tools several times a week or daily, primarily for writing, grammar checking, and research purposes. Grammar and spell checkers are the most commonly used tools, reflecting the centrality of language-related academic tasks in the sample's disciplinary context.

Second, students hold strongly positive perceptions of AI's contribution to their learning and academic performance. However, these positive perceptions do not translate into statistically significant differences in self-reported grades. The disconnection between perceived benefit and measurable academic outcome suggests that AI tools may enhance the subjective experience of learning reducing cognitive load, increasing efficiency, and improving the quality of surface-level outputs without necessarily deepening the substantive learning 2. that determines grades.

Third, instructor encouragement plays a statistically significant role in both AI usage frequency and students' future use intentions. Notably, it is the strength and positivity of instructor encouragement not merely the provision of guidance that predicts these outcomes. This finding has direct implications for faculty development and institutional AI policy.

Fourth, while the majority of students do not perceive themselves as dependent on AI, frequent users exhibit significantly higher dependency perceptions and lower confidence in independent essay writing. This association signals an emerging risk that warrants proactive intervention.

Fifth, awareness of AI risks and limitations is nearly universal among respondents, regardless of instructor guidance. This suggests that students are arriving in classrooms with pre-existing digital literacy, though the depth and accuracy of this awareness remain open questions.

RECOMMENDATIONS

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

Instructors should adopt an active, structured approach to AI integration in their courses. Rather than merely permitting or prohibiting AI use, faculty should design learning activities that scaffold productive AI engagement for example, requiring students to critically evaluate AI-generated outputs, use AI as a brainstorming tool rather than a final-product generator, and document their AI-assisted workflow. The significant association between instructor encouragement and student behavior underscores the leverage educators possess.

Higher education institutions should develop comprehensive AI literacy programs that go beyond surface-level awareness of risks. These programs should address the metacognitive skills needed to use AI effectively without eroding independent competence. Institutions should also invest in faculty training to equip instructors with the knowledge and confidence to guide students' AI use.

Subsequent studies should employ longitudinal designs to track changes in AI dependency and self-efficacy over time. The use of objective academic performance measures rather than self-reported grades would strengthen the validity of findings. Qualitative methods such as in-depth interviews or reflective journals should complement quantitative approaches to capture the nuanced ways students conceptualize and narrate their relationship with AI tools.

LIMITATIONS

This study has several limitations that should be acknowledged. The use of convenience sampling limits the generalizability of findings to the broader student population. Self-reported grades may be subject to social desirability bias and recall error. The cross-sectional design precludes causal inferences. The overwhelmingly positive sentiment toward AI (with very few dissenting respondents) may reflect sample characteristics rather than a universal trend. Finally, the study focused on quantitative patterns; the open-ended narratives that could illuminate the qualitative dimensions of students' AI experiences were not systematically analyzed.

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