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Generative AI Use, Perceived Learning, and Perceived Academic Performance Among University Students

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Abstract— Generative AI tools are increasingly embedded in university study practices, yet institution-level evidence remains limited, particularly in underrepresented regions. This study examined the frequency and patterns of AI use among undergraduates at Maaref University of Applied Sciences in northern Syria and explored its relationship with perceived understanding, academic performance, attitudes, and concerns. An online questionnaire was completed by 58 students from seven faculties, and data were analyzed using descriptive statistics, correlations, t-tests, ANOVA, and multiple regression. Most respondents (81.0%) used AI daily or several times weekly, with ChatGPT the most commonly reported tool. AI use was positively associated with perceived understanding ($r = .677$, $p < .001$) and academic performance ($r = .765$, $p < .001$). The regression model explained 72.1% of the variance in perceived academic performance. Although causal conclusions cannot be drawn, the findings support structured AI-literacy training, verification practices, and clear institutional guidance for responsible academic use.

Keywords— artificial intelligence, higher education, ChatGPT, student learning, perceived academic performance, technology acceptance, academic integrity.

Introduction

Ten years ago, artificial intelligence belonged largely to computer science faculties. It has since spread through everyday life, and education has been pulled into that spread along with everything else (Crompton & Burke, 2024; Harry & Sayudin, 2023). What sets the current generation of tools apart is that they do not simply deliver fixed content. They write, clarify, summarize, and answer open questions in plain language, which puts them in the middle of reading comprehension, problem-solving, and writing tasks (Albadarin et al., 2024; Tlili et al., 2023).

The appeal rests on two features. The answer arrives at once, and it reads as though it were written for the person who asked rather than assembled for a lecture hall of two hundred (Harry & Sayudin, 2023; Vieriu & Petrea, 2025). University students turn to ChatGPT, Gemini, and Copilot to untangle material they find confusing, to complete assignments, to generate ideas, and to revise for examinations (Hassan, 2026; Tamimi et al., 2024; Vieriu & Petrea, 2025). Secondary school students do much the same with homework and classwork (Tamimi et al., 2024). Nor is the behavior confined to a single cohort. Cross-sectional data gathered recently in Malaysia, Slovenia, Romania, Spain, and India place AI use across academic levels, faculties, and fields of study, with adoption running from about two-thirds of a sample to nearly all of it, depending on who was surveyed (Bokan et al., 2026; Fošner, 2024; Morell-Mengual et al., 2025; Phua et al., 2025; Vieriu & Petrea, 2025).

Growth on this scale has drawn objections. One line of concern holds that heavy reliance on AI may wear away a student's capacity to think without it; a second questions how far the output can be trusted; a third asks what academic honesty means once part of an answer has been drafted by a chatbot (Hassan, 2026; Tamimi et al., 2024; Tlili et al., 2023). Working in Nigerian tertiary institutions, Abubakar et al. (2024) take the argument further. In their reading, AI now occupies so much of the space around assignments, research, and examinations that conventional assessment can no longer measure what it claims to measure, and the appropriate response is to redesign assessment rather than absorb the disruption in silence. Elsayed et al. (2024) report something related but separate. Their AI-assisted examinations delivered genuine benefits only where a teacher remained actively involved; withdraw the teacher and both the reduction in anxiety and the gain in outcomes largely disappeared. Crawford et al. (2024) complicate matters again. In an Australian sample, AI use bore no significant direct relationship to perceived grade average, yet a negative indirect effect ran through weakened social support and wellbeing. Whatever AI gives academically, it may quietly take back in ways that are harder to see.

One question sits at the center of the field unanswered: does using AI genuinely deepen comprehension and raise attainment, or does it mainly rearrange study habits and leave results roughly where they were (Hassan, 2026; Vieriu & Petrea, 2025)? The tools themselves keep changing, which obliges the evidence to keep changing with them. What remains missing is a sharper account of what students do with these systems from one day to the next, and whether any of it pays off (Hassan, 2026; Jo, 2024). Existing reviews do not resolve this neatly. Albadarin et al. (2024) portray ChatGPT functioning capably as a helper available on demand, quick with feedback and with explanations of difficult topics, but several studies in their review noted a price: heavy use seemed to blunt inventive thinking and weaken collaboration in groups. Crompton and Burke (2024) reach a similarly divided verdict, setting round-the-clock availability and personalized feedback against inaccuracy, bias, and misuse.

The present paper adds primary survey evidence from 58 undergraduates across seven faculties at Maaref University of Applied Sciences. Its framing borrows loosely from technology-acceptance reasoning, in which perceived usefulness and perceived ease of use govern whether a technology is taken up at all (Chew et al., 2025; Jo, 2024). On that basis we treat AI usage, perceived understanding, perceived academic performance, and general attitudes toward AI as connected but analytically distinct variables, and we test statistically how they move in relation to one another. The purpose is practical. One institution gains concrete evidence to work from when it designs AI-literacy training, makes curriculum decisions, and writes usage policy.

The study is grounded more specifically in the Technology Acceptance Model (TAM) and its extension, the Unified Theory of Acceptance and Use of Technology (UTAUT), both of which posit that the adoption and continued use of a technology are governed primarily by its perceived usefulness and perceived ease of use, with downstream consequences for attitudes, behavioral intentions, and performance-related outcomes. In the present design, the AI Usage scale (Section B) operationalizes behavioral engagement with the technology; the Understanding scale (Section C) and the Perceived Academic Performance scale (Section D) capture outcome variables that TAM and UTAUT predict should be positively associated with use; the Perceptions of AI in Education scale (Section E) indexes attitudinal appraisal alongside usefulness and ease-of-use judgments; and the Concerns and Ethics scale (Section F) reflects perceived risk, which later TAM and UTAUT extensions and recent applications in educational AI research (Phua et al., 2025) treat as a relevant boundary condition on the use–outcome relationship. Mapping the empirical constructs of the present study onto this framework provides a coherent conceptual foundation for the regression model and a theoretical basis for interpreting the coexistence of favorable appraisals and substantial concerns that the data reveal.

The study provides institution-level evidence from a relatively underrepresented higher-education context showing that frequent generative AI use is strongly associated with students' perceived understanding and perceived academic performance, while frequent users simultaneously report substantial concerns regarding accuracy, over-reliance, and the need for institutional guidance.

1.1 Problem Statement

A paradox has taken shape as generative AI has worked its way into higher education. Adoption is no longer experimental. Cross-sectional surveys conducted recently place the proportion of undergraduates using AI for academic work somewhere between about two-thirds and nearly the whole sample, a large share of them using it daily or several times a week (Bokan et al., 2026; Fošner, 2024; Phua et al., 2025; Vieriu & Petrea, 2025). Institutions, meanwhile, have been slow to put in place the assessment structures, the usage policies, and the literacy training that adoption at this scale requires

(Abubakar et al., 2024; Fošner, 2024; Malik et al., 2023).

The problem is not only administrative. Underneath it lie empirical questions that remain open. Does AI use represent real cognitive engagement, or a thinner form of reliance in which the task is simply handed off (Tortella et al., 2025; Zakir et al., 2026)? Are the academic gains students describe actual learning, or faster completion of work that happens to be assessed (Chew et al., 2025; Jaafar et al., 2025)? And how are questions of trust, accuracy, and academic integrity to be squared with a technology students already use constantly, whatever their institution has or has not told them (Bokan et al., 2026; Sunmboye et al., 2025; Zhou et al., 2024)? The evidence on trust pulls in two directions. In one recent medical-education sample, most students judged AI output reliable (Bokan et al., 2026), and yet accuracy and verification came up more often than any other worry in nearly every population surveyed (Jaafar et al., 2025; Tortella et al., 2025). There is a geographical imbalance as well. Most of what has been published comes from North America, East Asia, and a growing body of work in South and Southeast Asia and Europe, while quantitative, institution-level research from the Middle East and North Africa that ties usage, perceived comprehension, perceived academic performance, and concerns to a single sample is comparatively rare. The present study takes up that gap. It measures these constructs together in one under-represented institutional setting and tests statistically how they relate, instead of reporting each as a descriptive figure standing on its own.

1.2 Research Objectives

This study examines the extent and patterns of students' use of artificial intelligence (AI) tools in the learning process and identifies the AI tools most frequently used for academic purposes. It also looks at students' perceptions of the contribution of AI to their understanding of course content, examines the association between AI use and perceived academic performance, and studies students' attitudes toward the integration of AI in education, with attention to their perceived benefits, challenges, concerns, and expectations regarding its use as a learning support tool.

1.3 Research Questions

1. How frequently do undergraduate students use generative AI tools in their academic work?
2. Which generative AI tools do students report using most often for academic purposes?
3. How do students perceive the contribution of generative AI to their understanding of course content?
4. What is the relationship between generative AI use and students' perceived academic performance?
5. How do students evaluate the integration of generative AI in higher education, and what concerns, if any, do they associate with its use?

2. Literature Review

2.1 The Growing Presence of AI in Higher Education

There is an obvious reason AI keeps appearing in education research. It answers questions, works through material step by step, and supports schoolwork in ways that used to require a person being available to ask. As the underlying systems improved, schools and universities took them up more thoroughly, and getting help stopped being something a student had to arrange in advance (Harry & Sayudin, 2023). That change, above all, is what has drawn researchers toward questions about how AI alters learning, academic outcomes, and students' attitudes toward technology inside their coursework.

Newer evidence indicates that AI has moved beyond occasional use into ordinary student life. Among Romanian engineering students, Vieriu and Petrea (2025) recorded 95.6% who had used AI technologies for academic activities, 57.6% of them weekly and 18.8% daily. Phua et al. (2025) encountered no exceptions at all: every student in their Malaysian university sample, 100%, reported experience with AI tools. Bokan et al. (2026) put usage at 91.6% among Indian medical students, with 56.9% weekly and 12.5% daily users. Slovenian students show similarly broad use in Fošner (2024) data, although frequency shifted with field of study and academic level. Uniformity, however, is absent. Tortella et al. (2025) found that 53.7% of Italian physiotherapy students had never once used an AI chatbot for academic purposes, even though 95.3% knew such tools existed, and Sunmboye et al. (2025) observed that first-year UK medical students leaned on AI more heavily than their seniors. The picture that emerges is one of wide but uneven use, varying by discipline, by institution, and by stage of study. The faculty- and year-level breakdown reported below speaks to exactly that.

2.2 AI Tools Used by Students and Patterns of Engagement

Part of the reason AI spread so quickly is quantity: there is far more of it than there used to be. Chatbots of the ChatGPT type field questions and work through hard material, while other applications help students locate information or get through assignments faster (Tlili et al., 2023). Treating ChatGPT's early uptake as a case study, Tlili et al. (2023) found the public discussion largely enthusiastic, with a more guarded minority raising the quality of responses, dependence, and ethics. That same split reappears throughout this literature. Reviewing 14 empirical studies, Albadarin et al. (2024) described students using ChatGPT much as they would a continuously available, on-demand assistant: feedback on demand, fast explanations, help with drafting and with generating ideas. Several of the studies they examined nonetheless warned that overuse might wear down inventive thinking and the capacity to work with others. The larger review by Crompton and Burke (2024), covering 44 studies, listed eight separate ways students used ChatGPT, among them support at any hour, help unpacking difficult concepts, conversational practice, and personalized feedback. Against these they set real drawbacks: factual error, bias, and plagiarism.

Quantitative studies published since have not disturbed ChatGPT's lead. In Malaysian, Iraqi, and Indian medical student samples respectively, Phua et al. (2025), Jaafar et al. (2025), and Bokan et al. (2026) each identify ChatGPT as the tool used most. In a study of 974 Spanish university students, Morell-Mengual et al. (2025) reported that 61.4% of participants used generative AI chatbots, with ChatGPT being the most commonly used tool. Students primarily reported using these technologies to facilitate their understanding of complex concepts, manage their study time more effectively, and improve their perceived academic performance. However, despite these perceived benefits, participants also expressed concerns about becoming overly dependent on AI and the potential negative effects of its use on the development of writing and analytical skills. Virtual assistants taken as a whole, a category covering ChatGPT, Siri, and Google Assistant, reached 88.2% of the sample studied by Vieriu and Petrea (2025). One dominant general-purpose tool trailed by a longer tail of specialized ones, Grammarly for writing and Perplexity for search among them, is a shape that repeats in almost every population studied. The tool breakdown obtained here matches it.

2.3 AI and Comprehension of Course Material

Comprehension is probably where AI gets its warmest reviews. Harry and Sayudin (2023) describe it as able to locate precisely where a particular student has become stuck and to reshape its explanation accordingly, instead of delivering one script to a whole class. Students in the study of Vieriu and Petrea (2025) used AI to simplify dense material, to organize notes, and to work through research more efficiently. Crompton and Burke's (2024) review found the same thing, with explanation of concepts and permanent availability among the uses reported most often.

More recent quantitative work sharpens the claim. Bokan et al. (2026) recorded 76.5% of Indian medical students agreeing or strongly agreeing that AI tools helped them grasp difficult concepts, and 88.2% saying this was their main reason for using AI at all. Iraqi medical students in Jaafar et al.'s (2025) study reported measurable gains in understanding their subjects: 39.9% described moderate improvement and 24.7% significant improvement. In a structural equation model built at a Mexican university, González et al. (2026) found AI use exerting a positive and significant effect on learning outcomes through gains in academic autonomy, comprehension of content, motivation, and engagement ($\beta = .439$, $p < .001$). Nursing students in Pakistan, according to Zakir et al. (2026), showed a moderate positive correlation between real-time interaction with AI and their learning experience ($r = .547$, $p < .001$). Across these studies the strength reported most consistently is comprehension, supported by feedback that arrives immediately. The item-level results reported below reproduce that pattern.

2.4 AI, Feedback, and Perceived Academic Performance

Whether any of this converts into measurable outcomes is a harder question and a separate one. Jo (2024), studying what drives university students to adopt ChatGPT, linked its personalization and self-learning features to stronger knowledge acquisition, which in turn shaped how useful students judged the tool to be and whether they intended to go on using it. The result is consistent with technology-acceptance theory. Elsayed et al. (2024), working with language learners in a quasi-experiment, found that AI-assisted examinations lowered demotivation and anxiety and improved outcomes so long as a teacher was genuinely involved. When teacher involvement was removed, most of these benefits disappeared.

Cross-sectional and structural-equation studies published lately lend broad support to a positive association between AI and performance, though most attach conditions. González et al. (2026) measured a positive direct effect of AI use on perceived academic performance ($\beta = .524$, $p < .001$), with learning outcomes carrying a large part of that relationship ($\beta = .781$, $p < .001$). In Vieriu and Petrea's (2025) sample, 82.4% believed AI use had contributed to better perceived academic performance. Shahzad, Xu, Lim, et al. (2024) found that AI use and social-media use both positively predicted perceived academic performance among Chinese university students, mediated by smart learning. Jaafar et al. (2025) recorded self-assessed grade improvement in 28.3% of Iraqi medical students after using AI, against decline in 8.5%. Among Malaysian undergraduates, Chew et al. (2025) reported positive correlations with perceived academic performance for perceived usefulness, ease of use, attitude, and behavioral intention alike, the firmest of them running through perceived ease of use.

Hassan (2026) makes a related argument: by taking over the routine task of locating and retrieving information, AI can release time for analysis, revision, and problem-solving. That gain, though, depends on AI use being structured. Unguided use, on Hassan's reading, generally did nothing for performance and could actively undermine problem-solving in summative assessment.

The picture is not uniformly favorable. In the Australian sample examined by Crawford et al. (2024), AI usage had no significant direct effect on perceived grade average. What appeared instead was a negative indirect effect running through reduced social support and wellbeing: students who felt more socially supported by AI than by other people reported weaker grade performance. The finding is a useful counterweight. It implies that the relationship between AI and performance turns on how the technology is used and on what it replaces, and that exposure by itself guarantees nothing. Throughout this literature runs the same caution. AI is there to support learning, not to stand in for the effort and judgment that learning requires (Vieriu & Petrea, 2025).

2.5 Student Perceptions, Ethical Concerns, and Calls for Guidelines

Even researchers who acknowledge what AI offers raise objections they regard as impossible to wave away. Over-reliance may weaken independent learning and critical thinking, and open questions remain about the accuracy of what these tools produce and about what academic honesty amounts to once a chatbot has been involved (Tamimi et al., 2024; Hassan, 2026). Abubakar et al. (2024) argue that AI's expanding place in assignments, research, and examination preparation already strains the capacity of conventional assessment to show what a student actually knows. Their remedy has three parts: explicit policies on use, fairer access to the technology, and assessment redesigned around critical thinking rather than around tasks a chatbot completes in seconds. Tlili et al. (2023) put a comparable tension in different terms, presenting ChatGPT as capable of being either an asset or a liability.

Survey evidence published since has brought this mixture of enthusiasm and caution into clearer focus. Iraqi medical students in Jaafar et al.'s (2025) study rated AI well on ease of use (85% agreed) and on time saved (82.8% agreed), while 45% would commit themselves neither way on reliability.

Bokan et al. (2026) found 70.7% of Indian medical students judging AI output good or reliable at the same time as 72.1% worried about accuracy and 50.2% about data privacy. In that sample, approval and anxiety were not alternatives; they traveled together. Drawing on the Technology Acceptance Model and the General Attitudes towards AI Scale, Phua et al. (2025) similarly recorded high engagement driven by perceived usefulness and ease of use, accompanied by substantial worry about security, privacy, and the possibility that over-reliance would undercut critical thinking and problem-solving.

Academic integrity and the absence of clear guidelines surface repeatedly in the student and instructor accounts of AI-assisted writing collected by Malik et al. (2023) and Zhou et al. (2024). Misinformation and factual error stand out as the main obstacles to trust in the work of Tortella et al. (2025) and Sunmboye et al. (2025). Lin and Chen (2024) report a further wrinkle: AI-integrated educational applications stimulated creativity and engagement for many students, yet also imposed rigid frameworks that narrowed creative thinking and raised performance anxiety through relentless algorithmic assessment. Among Hong Kong university students, Chan and Hu (2023) recorded broadly positive attitudes toward generative AI in teaching and learning, qualified by reservations about accuracy, privacy, ethics, and personal development. That combination is barely distinguishable from what Bokan et al. (2026) documented two years later in an entirely different national setting. One conviction runs through all of it: AI should remain a means of support, and students remain answerable for checking its output and for doing their own thinking.

2.6 Summary and Research Gap

Several threads run through the research reviewed above. Student use of AI is widespread and still growing; recent cross-sectional work puts adoption between roughly two-thirds and effectively everyone, depending on the population sampled (Bokan et al., 2026; Fošner, 2024; Phua et al., 2025; Tamimi et al., 2024; Vieriu & Petrea, 2025).

A fairly small group of general-purpose tools, ChatGPT above all, absorbs most of that use (Albadarin et al., 2024; Crompton & Burke, 2024; Jaafar et al., 2025; Morell-Mengual et al., 2025; Phua et al., 2025; Tlili et al., 2023). Students describe real value in the areas of comprehension and feedback (Bokan et al., 2026; González et al., 2026; Harry & Sayudin, 2023; Vieriu & Petrea, 2025; Zakir et al., 2026).

The link to perceived academic performance looks genuine but conditional, hedged about by whether a teacher stays involved, whether use is structured or unguided, and whether AI supplements human support or replaces it (Chew et al., 2025; Crawford et al., 2024; Elsayed et al., 2024; González et al., 2026; Hassan, 2026; Jo, 2024).

Its spread has raised defensible concerns about over-reliance, accuracy, privacy, and the integrity of assessment, and has produced calls for clearer institutional guidelines in settings as unlike one another as Nigeria, Italy, Hong Kong, and Slovenia (Abubakar et al., 2024; Chan & Hu, 2023; Fošner, 2024; Malik et al., 2023; Tlili et al., 2023; Tortella et al., 2025; Zhou et al., 2024).

What appears far less often is quantitative evidence at the level of a single institution that captures usage, understanding, performance, perceptions, and concerns in one sample and then tests statistically how they hang together. From the Middle East and North Africa such evidence is scarcer still, set against the growing body of comparable work coming out of Southeast Asia, South Asia, and Europe. Filling that gap is what this study sets out to do.

3. Methodology

3.1 Research Design

A cross-sectional quantitative survey was used to examine how university students use AI and how they understand its connection to their own learning and academic results.

A descriptive-correlational design fitted that purpose, since it is built to capture patterns of use, the particular tools students choose, and attitudes across a defined group at one point in time. Comparable recent surveys of AI use in higher education have taken the same approach (Bokan et al., 2026; Fošner, 2024; Jaafar et al., 2025; Vieriu & Petrea, 2025). Data were gathered through a self-administered online questionnaire.

3.2 Setting and Sample

Undergraduate students at Maaref University of Applied Sciences made up the participant pool. Fifty-eight valid responses (N = 58) were returned by respondents drawn from seven faculties, most of them in Pharmacy, Arts, Engineering, and Chemistry, with smaller numbers from Business, Science, and elsewhere. Men accounted for 55.2% of the sample (n = 32) and women for 44.8% (n = 26). Exactly half the respondents (50.0%) were aged 19 to 20, and the sample was junior in academic terms as well: 51.7% were in their first year and 41.4% in their second.

Self-reported GPA was distributed fairly evenly, the largest groups falling in the 3.0–3.49 band (29.3%) and the 2.5–2.99 band (27.6%). Table 1 sets out the complete breakdown. Sampling was by convenience, approaching students who were reachable and willing, chiefly because this made it possible to collect a workable number of responses in the time available. The trade-off is a limit on how far the findings travel, a point taken up again in Section 5.6.

Table 1. Sample Demographic Profile (N = 58).

Variable	Category	n	%
A1. Gender	Male	32	55.2
A1. Gender	Female	26	44.8
A2. Age	19–20	29	50.0
A2. Age	21–22	13	22.4
A2. Age	23 or above	9	15.5
A2. Age	17–18	7	12.1
A3. Faculty	Pharmacy	16	27.6
A3. Faculty	Arts	15	25.9
A3. Faculty	Engineering	12	20.7
A3. Faculty	chemistry	9	15.5
A3. Faculty	Other	4	6.9
A3. Faculty	Business	1	1.7
A3. Faculty	Science	1	1.7
A4. Year of Study	First	30	51.7
A4. Year of Study	Second	24	41.4
A4. Year of Study	Third	3	5.2
A4. Year of Study	Fifth or above	1	1.7
A5. Approximate GPA	3.0–3.49	17	29.3
A5. Approximate GPA	2.5–2.99	16	27.6
A5. Approximate GPA	2.0–2.49	15	25.9
A5. Approximate GPA	Less than 2.0	6	10.3
A5. Approximate GPA	3.5–4.0	4	6.9

3.3 Data Collection Procedure

Google Forms hosted the survey, which made students easy to reach and kept every response in one place. Similar studies on this topic have relied on comparable online platforms (Bokan et al., 2026; Vieriu & Petrea, 2025). All 58 completed responses came from students at Maaref University of Applied Sciences. Participation was voluntary, and students were told what the study was for before they began.

3.4 Research Instrument

The questionnaire had two parts. The first collected demographic information: gender, age, faculty, year of study, and approximate GPA. The second consisted of five Likert scales, each scored from 1 (Strongly Disagree) to 5 (Strongly Agree):

- Section B – AI Usage (7 items): how often and how widely AI was used for studying, examination preparation, and assignments.
- Section C – Understanding of Course Materials (7 items): the perceived effect of AI on comprehension, on clarity, and on independent learning.
- Section D – Perceived Academic Performance (6 items): the perceived effect of AI on grades, on the quality of coursework, and on examination preparation.
- Section E – Perceptions of AI in Education (7 items): attitudes toward integrating AI into higher education and toward its value there.
- Section F – Concerns and Ethics (6 items): awareness of over-reliance, of accuracy problems, and of the need for institutional guidelines.

3.4.1 Questionnaire Development and Validity

Items were adapted from instruments used in recent cross-sectional surveys of AI use among university students (Albadarin et al., 2024; Bokan et al., 2026; Phua et al., 2025; Vieriu & Petrea, 2025) and from the Technology Acceptance Model and the General Attitudes towards AI Scale tradition cited in those studies. Wording was revised to fit the local institutional context and to align each item unambiguously with one of the five target constructs (Usage, Understanding, Perceived Academic Performance, Perceptions of AI, and Concerns and Ethics). Content validity was examined by three faculty members with subject-matter expertise in educational technology and research methods, who reviewed each item for relevance, clarity, and construct fit. Items that two or more reviewers flagged were reworded or removed before data collection. Internal-consistency reliability was estimated after data collection using Cronbach's alpha for each scale (see Section 4.2). The Concerns and Ethics scale returned a marginal reliability coefficient (α = .61), which suggests that the items in that section may not tap a single underlying construct. Accordingly, the Concerns and Ethics items should be interpreted with caution and, where appropriate, treated as individual indicators rather than as a composite score; future work is encouraged to disaggregate concerns about accuracy and verification from concerns about over-reliance and to evaluate the resulting subscales separately.

Several further items completed the instrument. Single- and multi-select questions asked which AI tools students used and how frequently, and which types of course they relied on AI for most. Two open-ended prompts asked students to name the greatest benefit AI had brought them and the specific course in which it had helped most.

3.5 Data Analysis

Likert responses were coded from 1 to 5 and averaged within each scale to produce composite scores, and the internal consistency of every scale was checked with Cronbach's alpha. Means, standard deviations, and frequencies were computed for each item and each composite. Pearson correlations were used to examine how the five composites related to one another. Scores were compared by gender using independent-samples t-tests, while a one-way ANOVA set academic-performance scores against the self-reported GPA bands. Multiple linear regression was then used to ask whether usage, understanding, and general perceptions, taken together, predicted perceived academic performance. Analyses were run in Python using pandas, SciPy, and statsmodels, with significance set at α = .05.

Before fitting the regression model, the assumptions of multiple linear regression were checked. Multicollinearity among predictors was examined using the Variance Inflation Factor (VIF) and tolerance statistics; predictors with VIF values exceeding 5 or tolerance values below 0.20 were flagged for review. Normality of residuals was assessed by visual inspection of histograms and normal Q–Q plots, supplemented by the Shapiro–Wilk test. Homoscedasticity was examined by plotting standardized residuals against standardized predicted values and by inspecting the Breusch–Pagan statistic. No assumption violations were severe enough to invalidate the model. For each regression coefficient, the unstandardized coefficient (B), standard error (SE), standardized coefficient (β), t-statistic, p-value, and the 95% confidence interval (95% CI) for B are reported, in line with current reporting standards for multiple regression in the social sciences.

3.6 Ethical Considerations

Participation was voluntary at every stage. No identifying information was collected apart from an optional self-reported name, and that name was removed from all reported results. Everything is presented in aggregate. The study protocol was reviewed and approved by the Research Ethics Committee of Maaref University of Applied Sciences (approval reference: MUAS-REC-2025-014); the approval covered the survey instrument, the recruitment procedure, and the data-handling plan. All participants received a written information sheet that described the purpose of the study, the voluntary nature of participation, the anonymous treatment of responses, and the absence of any direct benefit or penalty associated with taking part. Informed consent was obtained from every respondent through a mandatory consent item at the start of the online questionnaire; participants were explicitly informed that they could withdraw at any point before submitting the form and that withdrawn responses would not be retained. No identifying information was collected beyond an optional self-reported name, which was removed prior to analysis; responses are presented only in aggregate, and the raw dataset is stored on a password-protected institutional drive accessible only to the principal investigator, in accordance with the university's data-protection policy.

4. Results

Descriptive, correlational, and inferential results are reported below in the order of the five research questions, with the demographic comparisons following.

4.1 AI Usage Frequency and Tools (RQ1, RQ2)

Studying with AI several times a week or daily was reported by 81.0% of respondents, with a further group using it weekly and only a small minority saying they rarely used it at all (Figure 1).

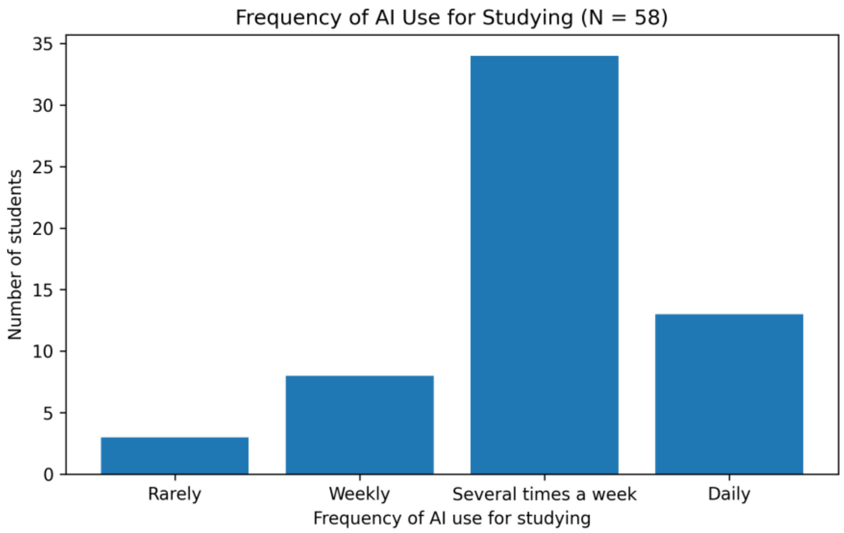

Figure 1. Frequency of AI Use for Studying (N = 58).

ChatGPT was named most often (74.1%), then Google Gemini (50.0%), an unspecified 'Other' category (29.0%), Claude (19.0%), Grammarly (9.0%), Microsoft Copilot (7.0%), and Perplexity AI (5.0%; Figure 2). Because the question permitted multiple responses, many students reported using more than one tool; ChatGPT together with Gemini was the pairing that came up most. Recent multi-tool surveys describe the same cross-tool behavior (Morell-Mengual et al., 2025).

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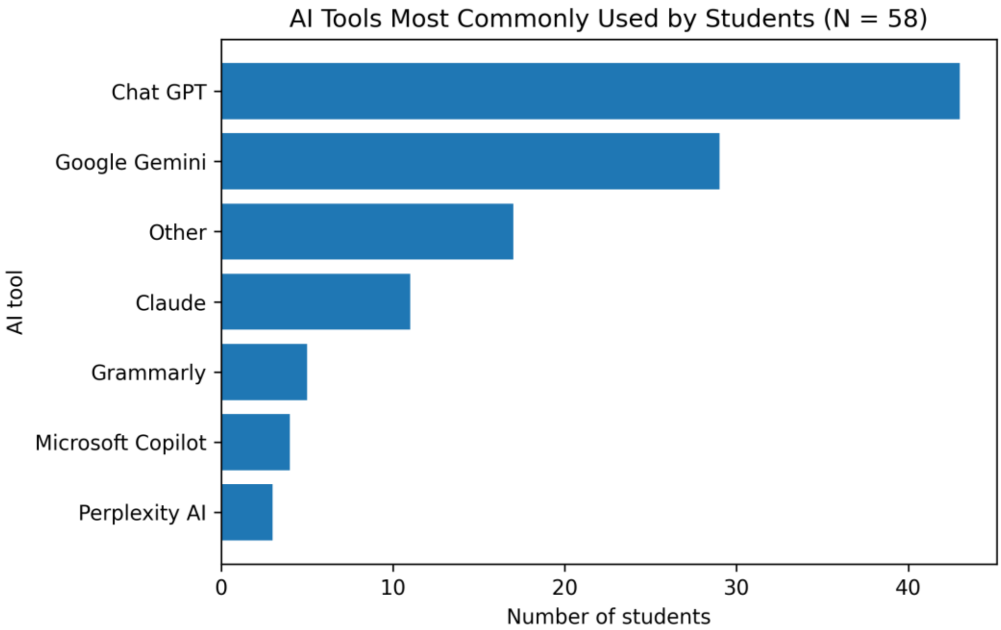

Figure 2. AI Tools Most Commonly Used by Students (N = 58). Note. Multiple responses were permitted.

4.2 Composite Construct Scores and Reliability

All five scales showed acceptable to good internal consistency except the Concerns/Ethics scale, which was marginal (α = .61). Table 2 reports reliability coefficients and composite descriptive statistics calculated directly from the supplied dataset.

Table 2. Composite Construct Reliability and Descriptive Statistics (N = 58).

Construct	Items	Cronbach's α	M	SD
AI Usage (B)	7	0.77	4.03	0.60
Understanding (C)	7	0.79	3.93	0.59
Perceived Academic Performance (D)	6	0.81	3.99	0.57
Perceptions of AI (E)	7	0.84	4.15	0.61
Concerns/Ethics (F)	6	0.61	3.95	0.51

4.3 Correlations Among Constructs

All five composites were positively correlated. Usage correlated strongly with perceived understanding ($r = 0.677$, $p < .001$) and perceived academic performance ($r = 0.765$, $p < .001$). Understanding and performance were also strongly related ($r = 0.746$, $p < .001$). Perceptions correlated positively with all other constructs, while Concerns/Ethics showed weaker positive associations with usage ($r = 0.474$) and understanding ($r = 0.476$).

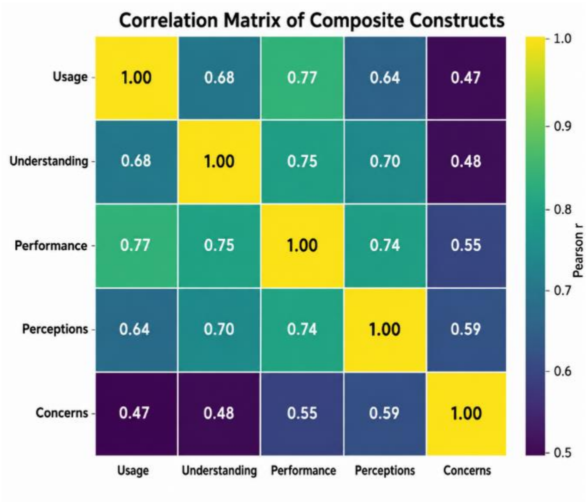

Figure 5. Correlation Matrix of Composite Constructs.

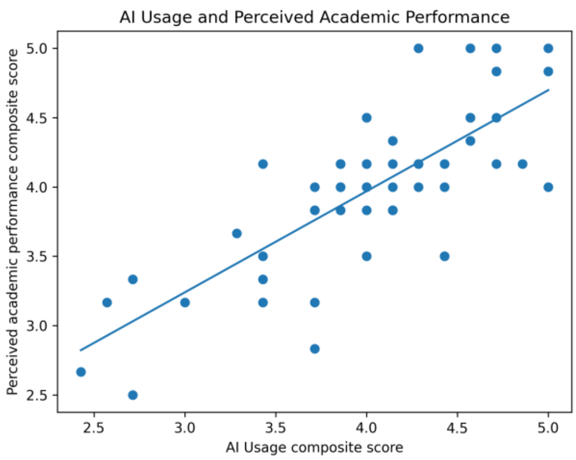

Figure 6. Relationship Between AI Usage and Perceived Academic Performance.

Construct	Usage (B)	Understanding (C)	Performance (D)	Perceptions (E)	Concerns (F)
Usage (B)	—	0.68	0.77	0.64	0.47
Understanding (C)	0.68	—	0.75	0.70	0.48
Performance (D)	0.77	0.75	—	0.74	0.55
Perceptions (E)	0.64	0.70	0.74	—	0.59
Concerns (F)	0.47	0.48	0.55	0.59	—

Table 3. Pearson Correlations Among Composite Constructs (N = 58).

4.4 Multiple Linear Regression Predicting Perceived Academic Performance (RQ4)

Multiple linear regression was used to examine whether AI usage, perceived understanding, and general perceptions of AI predicted perceived academic performance. The model was statistically significant, $F(3, 54) = 46.40$, $p < .001$, explaining 72.1% of the variance ($R^2 = 0.721$, adjusted $R^2 = 0.705$). All three predictors were statistically significant: AI usage ($\beta = 0.391$, $p < .001$), understanding ($\beta = 0.277$, $p = .016$), and perceptions ($\beta = 0.292$, $p = .008$).

Table 5. Multiple Linear Regression Predicting Perceived Academic Performance.

Predictor	B	SE	β	t	p
B	0.373	0.098	0.391	3.800	0.000
C	0.266	0.107	0.277	2.497	0.016
E	0.273	0.099	0.292	2.760	0.008

4.5 Item-Level Patterns for Understanding and Performance (RQ3, RQ4)

Item-level results show the highest understanding ratings for rapid access to information and clarification of difficult topics, while ratings for critical thinking and independent learning were comparatively lower but remained above the scale midpoint (Figure 3). On the performance scale, task-specific items received higher ratings than the global statement that AI had improved perceived academic performance; 65.5% of respondents agreed or strongly agreed with the latter (Figure 4).

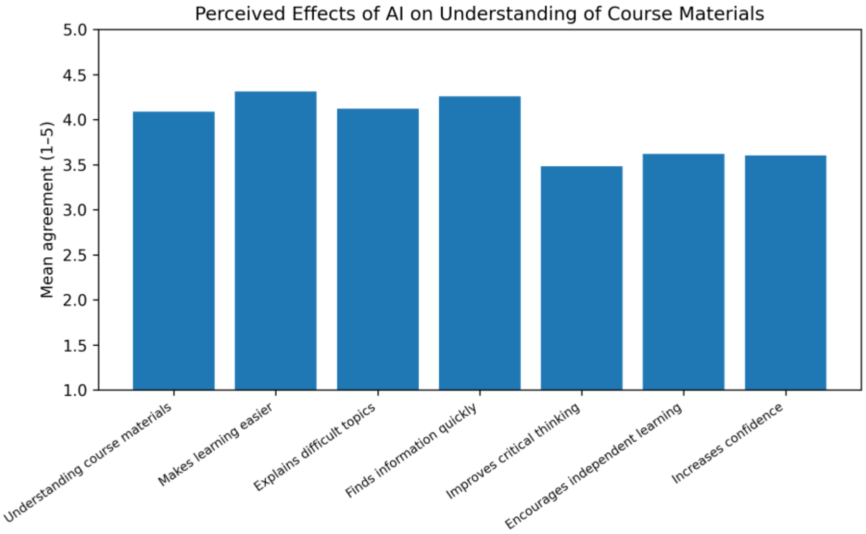

Figure 3. Perceived Effects of AI on Understanding of Course Materials.

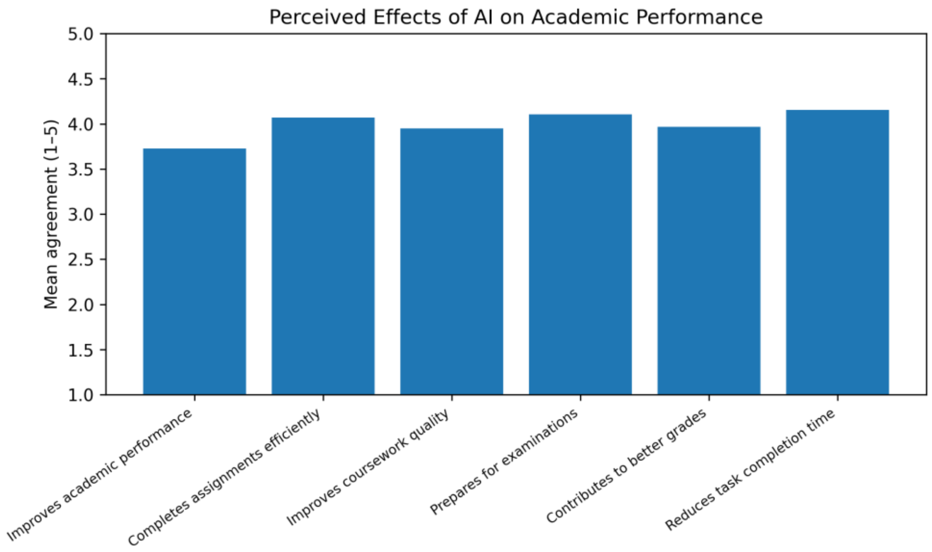

Figure 4. Perceived Effects of AI on Perceived Academic Performance.

4.6 Perceptions and Concerns (RQ5)

Of the five composites, Perceptions of AI in Education scored highest (M = 4.15). Agreement was particularly strong on two statements: that AI functions as an effective learning assistant, and that institutions ought to train students in its use. The Concerns/Ethics composite also fell above the scale midpoint (M = 3.78). Most students agreed both that heavy AI use could weaken independent thinking and that clearer institutional guidelines were needed.

4.7 Demographic and Contextual Comparisons

Independent-samples t-tests revealed no significant gender difference on the usage, understanding, or performance composites. The difference in perceptions of AI came close to conventional significance without reaching it: women scored somewhat higher (M = 4.31, SD = 0.51) than men (M = 4.02, SD = 0.66), $t(55.8) = -1.89$, $p = .063$ (Table 4).

Construct	**Male M (SD)**	**Female M (SD)**	**t**	**p**
B	3.99 (0.67)	4.09 (0.49)	-0.70	0.489
C	3.82 (0.57)	4.06 (0.60)	-1.57	0.122
D	3.94 (0.60)	4.06 (0.53)	-0.85	0.397
E	4.02 (0.66)	4.31 (0.51)	-1.89	0.063

Table 4. Composite Scores by Gender

A one-way ANOVA on perceived academic performance across the five GPA bands returned nothing significant, $F(4, 53) = 0.94$, $p = .446$. The benefit students reported bore no relation to where they stood academically. On course context, 43.1% used AI about equally in theoretical and practical courses, 34.5% mainly in theoretical courses, 13.8% mainly in practical or laboratory courses, and 8.6% hardly used it in any course.

5. Discussion

The aim was to record how often students use AI to study and which tools they use, then to test whether that use aligns with perceived gains in understanding and performance and with favorable attitudes toward AI in education. The analysis produced a reasonably coherent account. Use in this sample is frequent and widespread, attitudes lean strongly positive, and usage, understanding, and general perceptions between them account for a large share of the variance in perceived academic performance.

Rather than treating the variance explained in the regression as evidence that AI use improves perceived academic performance, the more useful reading is that the same students who report high familiarity and frequent use are also the ones who report high perceived benefit and high concern at the same time. The pattern is one of perceived utility and perceived risk coexisting in the most engaged users, and the analysis below is organised around that reading.

5.1 Extent and Tools of AI Use (RQ1 and RQ2)

That four students in five use AI several times a week or more belongs to a larger pattern already on record elsewhere, in which generative AI has become a study companion rather than a novelty that passes. Frequent and sometimes daily use has been documented among university students in Slovenia, Romania, India, and Malaysia (Bokan et al., 2026; Fošner, 2024; Phua et al., 2025; Vieriu & Petrea, 2025). ChatGPT's lead here (74.1%), with Gemini (50.0%) and Claude (19.0%) behind it, fits these being the most heavily marketed general-purpose tools freely available when the data were collected. It also matches earlier findings that put ChatGPT first across populations as different as Iraqi medical students and Spanish undergraduates (Jaafar et al., 2025; Morell-Mengual et al., 2025; Phua et al., 2025). Enough students combined tools, ChatGPT with Gemini in particular, to indicate that loyalty to one platform is not the norm. The likely explanation is that they cross-check answers or exploit what each tool does best, behavior also observed among Spanish students, who averaged more than two tools apiece (Morell-Mengual et al., 2025). One practical conclusion follows. AI-literacy training serves students better when it is tool-agnostic than when it is built around a single product (Crompton & Burke, 2024).

5.2 AI and Understanding of Course Material (RQ3)

Students rated AI highest for fast access to information and for understanding course material, and lower, though still positively, for building critical thinking and independent learning. The gap matters. It suggests that AI is treated principally as an aid to information and comprehension rather than as something that develops higher-order thinking by itself. Harry and Sayudin (2023) and Crompton and Burke (2024) flagged the same division, and Bokan et al. (2026) reproduced it almost item for item: 88.2% of their Indian medical students used AI mainly to understand difficult topics, and gains in comprehension outran gains in independent thought. Behind this lies an old worry in educational technology about where the line falls between a tool that scaffolds learning and a tool that quietly does the work learning is supposed to require. The concern-scale responses in this sample point the same way, with most students agreeing that heavy AI use could weaken independent thinking.

5.3 AI and Perceived Academic Performance (RQ4)

A strong correlation between usage and perceived academic performance ($r = .765$), together with a regression in which usage, understanding, and perceptions explained 72.1% of the variance in perceived performance, points to a clear pattern. Students who use AI more, who understand material better as a result, and who regard it favorably also report performing better. This matches Jo's (2024) finding that the perceived usefulness of ChatGPT for acquiring knowledge moves with students' sense of its impact, the experimental evidence from Elsayed et al. (2024) that supported AI-assisted assessment is linked to better academic outcomes, and the structural-equation result of González et al. (2026), in which AI use predicts performance both directly and through learning outcomes. It also fits the self-reported grade gains recorded among Iraqi medical students, where 28.3% improved and 8.5% declined (Jaafar et al., 2025), and the strong link between perceived ease of use and perceived academic performance among Malaysian undergraduates (Chew et al., 2025).

The proportion of variance explained in this regression is substantial and indicates that the three predictors move together with students' perceived academic performance rather than establishing a causal effect of AI use on attainment. The interpretively more important finding is the qualitative pattern: students in this sample simultaneously report high perceived utility and high concern, and the analysis below takes that coexistence as its central observation rather than the magnitude of any single coefficient.

Precision is required at this point. Performance was measured with self-report items, 'AI has improved my academic performance' among them, and not with actual grades. What the data show is a strong relationship of perceived benefit, not evidence that AI use produces better grades. Crawford et al. (2024) reinforce the caution: in their Australian sample no significant direct relationship appeared between AI use and grade average, and the indirect path that did appear was negative, running through reduced social support. Self-reported benefit and objectively measured performance are not interchangeable, and what AI displaces may matter as much as what it provides. Students in the present sample appear to have been reasonably careful on this point. Agreement was weaker on the direct, global item (65.5%) than on the narrower task-level items, which is to say they credited AI with concrete gains in efficiency and quality while stopping short of crediting it with their academic success as a whole. Pairing measures of this kind with actual grade records, as Hassan (2026) and Zakir et al. (2026) both recommend, would go some way toward settling the causal question.

Because all constructs were measured with self-report Likert items completed in a single sitting, the possibility of common-method bias cannot be ruled out and should be considered as a factor that may have inflated the observed associations. The correlations and the regression coefficients should therefore be read as upper-bound estimates of the relationships that would be expected under more method-diverse measurement.

5.4 Student Perceptions and the Coexistence of Enthusiasm and Caution (RQ5)

Perceptions of AI in Education scored highest of the five constructs (M = 4.15), with the firmest agreement attaching to two propositions: that AI serves as an effective learning assistant, and that training students to use it falls to the institution. This is what technology-acceptance thinking would predict, since usefulness and ease of use drive the intention to go on using something (Jo, 2024), and it matches the large proportion of students who intend to keep using AI. Enthusiasm did not, however, displace concern. Worries about accuracy and over-reliance were widely held, and they correlated positively with both Perceptions and Usage rather than negatively. This is the central finding. Concern does not belong to the students who keep their distance from AI; it is concentrated among those who use it most. Bokan et al. (2026) found the same configuration, with high perceived reliability (70.7% rating outputs good or reliable) sitting alongside widespread concern about accuracy (72.1%) in one and the same sample, as did Jaafar et al. (2025), whose respondents agreed strongly about ease of use and time saved while remaining almost universally cautious about reliability.

Tlili et al. (2023) caught something similar when they described ChatGPT as help and hazard at once. The same reasoning supports the argument of Abubakar et al. (2024) that institutions should attach clear guidelines to AI adoption instead of treating enthusiasm and caution as though only one of them could be right. Fošner (2024), Malik et al. (2023), and Zhou et al. (2024) have since made the same call in three quite different national settings. The practical implication is that AI-literacy work should not be designed to persuade reluctant students to try AI. It should sharpen the evaluative skills of students who are already using it constantly.

5.5 Demographic and Contextual Patterns

No significant gender gap appeared in usage, understanding, or performance, and the difference in perceptions was marginal at best. Adoption here does not divide sharply along gender lines, which is worth noting given how unevenly some earlier technologies were taken up. Self-reported GPA showed no significant relationship with perceived performance benefit either. The perceived value of AI seems to spread fairly evenly across the achievement range rather than gathering among the strongest or the weakest students. Use also moved flexibly between theoretical courses and practical or laboratory ones, which suggests that AI has settled into general study habits instead of remaining tied to one type of coursework. Sunmboye et al. (2025) observed much the same thing, with integration cutting across course types and academic years, though with heavier reliance at earlier stages.

5.6 Limitations

Several things restrict how far these findings should be carried. Fifty-eight students drawn from a narrow set of faculties at a single institution leaves statistical power modest, particularly for faculty-level comparisons where some cells are very small; Business and Science each contributed exactly one respondent. Confidence in generalizing beyond this institution is correspondingly limited. Every construct, perceived academic performance included, came from self-report Likert items completed in a single sitting, and shared method variance of that kind can inflate the correlations reported here. Most of the comparative literature cited above carries the same limitation, resting as it does on self-report cross-sectional or structural-equation designs rather than on objective performance records (Hassan, 2026; Zakir et al., 2026). A cross-sectional design also cannot establish the direction of causality. Stronger students may simply use AI more skillfully; AI use may genuinely improve outcomes; or something else, general academic engagement for instance, may be driving both at once. Because sampling was by convenience, respondents were not randomly selected, and the sample tilted heavily toward first- and second-year students (93.1%), which restricts what can be said about students in later years or in graduate programs, Sunmboye et al. (2025) found to differ meaningfully in reliance. Finally, the weak reliability of the Concerns/Ethics scale (α = .61) suggests that the construct may bundle more than one thing together. Future work would probably do better to split it into subscales, separating concerns about accuracy and verification from concerns about over-reliance.

5.7 Implications and Recommendations

- Training in AI literacy is most useful when it is not tied to a single product. It should cover the reasoning common to using ChatGPT, Gemini, Claude, and other assistants effectively and critically (Crompton & Burke, 2024).
- Because worry about accuracy and over-reliance runs highest among the heaviest users, verification skills and safeguards for independent thinking should be aimed at frequent users rather than delivered once as an introduction for newcomers.
- Clear institutional rules on what counts as acceptable AI use in coursework and assessment are warranted, given how firmly students already back such rules while using the tools daily. This aligns with existing calls to redesign assessment for learning environments in which AI is present throughout (Abubakar et al., 2024; Malik et al., 2023).
- Since the benefits of AI-supported learning appear to depend on genuine scaffolding, institutions should consider how instructors accompany AI-assisted study and assessment instead of assuming that access to the tools is sufficient on its own (Elsayed et al., 2024; Hassan, 2026).
- Alongside the academic benefits, institutions should watch for the social costs of substituting AI for people, among them reduced contact with peers or instructors and a weaker sense of belonging. Crawford et al. (2024) show that AI used as a social substitute can carry a cost to wellbeing even where academic effects are neutral or positive.
- Future studies should combine self-report measures of this kind with objective performance records and adopt longitudinal or experimental designs to test whether the associations reported here reflect a real causal benefit.

6. Conclusion

AI tools have become an ordinary part of how the students surveyed here study, with ChatGPT in front and Gemini and Claude behind it, and with more than four in five using AI several times a week or more. That rate matches the wider body of recent cross-sectional evidence from Southeast Asia, South Asia, and Europe (Bokan et al., 2026; Fošner, 2024; Phua et al., 2025; Vieriu & Petrea, 2025). Students tie this use to a firmer grasp of course material and, more tentatively, to stronger perceived academic performance. Their views of AI's place in education are largely favorable, and they remain alert to inaccuracy and over-reliance. Enthusiasm paired with caution turns up in almost every student population studied recently, from Iraq to Italy to Hong Kong (Bokan et al., 2026; Chan & Hu, 2023; Jaafar et al., 2025; Tortella et al., 2025). Between them, usage, understanding, and general perceptions accounted for a large part of the variance in perceived academic performance, which indicates that these parts of the student experience with AI move together rather than separately. As AI works its way further into higher education, the case for institutions to move first grows stronger: structured AI-literacy training that is not built around one product, and clear rules of use that take students' existing enthusiasm as a starting point while developing the critical judgment these tools demand.

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The authors confirm that the manuscript is their original work, and if others’ works are used, they are properly cited/quoted.

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