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GENERATIVE AI KNOWLEDGE, ACADEMIC USE, PERCEIVED HELPFULNESS AND ATTITUDES AMONG UNDERGRADUATE STUDENTS AT A MALDIVIAN UNIVERSITY

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Abstract : Generative artificial intelligence (GenAI) is widely used in higher education, but evidence from Maldivian undergraduates remains limited. The study examined knowledge, academic use, perceived helpfulness, attitudes and perceived institutional guidance needs among undergraduates at the Faculty of Engineering, Science and Technology (FEST), Maldives National University (MNU). An anonymous cross-sectional online survey received 100 submissions; 98 met eligibility criteria and were included, including records with identical answer patterns. Item-level descriptive results, a five-item knowledge index, ten-task breadth, Kruskal–Wallis tests and Spearman correlations were examined. Previous GenAI use was reported by 97 students (99.0%). Mean knowledge score was 3.76 (SD = 1.12; KR-20 = .42), and mean utilization breadth was 5.04/10 activities (SD = 2.27). Knowledge differed by study year ($H(3) = 20.35$, $p < .001$), but utilization breadth did not ($p = .197$); the knowledge-utilization association was not significant ($\rho = -.184$, $p = .070$). Most respondents (91/98; 92.9%) wanted more university guidance on effective and responsible GenAI use; 53/98 (54.1%) disagreed that they felt well informed. Helpfulness ratings were available for only 71 respondents, and attitude items did not support a common scale. Near-universal reported use coexisted with uneven knowledge, differentiated risk perceptions and strong demand for institutional guidance. Sampling, measurement, and cross-sectional limitations restrict generalization.

IndexTerms **– Generative artificial intelligence; AI literacy; undergraduate education; academic use; student attitudes; institutional guidance**

I. INTRODUCTION

Generative artificial intelligence (GenAI) tools, including ChatGPT, Gemini and Copilot, can generate explanations, summaries, text, code, and other materials through conversational interfaces. Their accessibility has made them attractive for routine university work: explaining complex concepts, developing outlines, refining writing and generating preliminary ideas. These affordances have raised questions not only about adoption but also about whether users understand the systems' limitations and how they judge their academic value (Chan and Hu, 2023; Walter, 2024).

Potential benefits coexist with concerns about inaccurate or fabricated information, privacy, bias, copyright, assessment integrity and overreliance. Students may view GenAI as useful while distrusting its factual accuracy; frequent exposure is not necessarily evidence of informed or critical use (Köhler and Hartig, 2024; Zhai et al., 2024). Institutions therefore need more precise knowledge of what students know, what they do, which tasks they find helpful and which risks they recognize. UNESCO (2023) advocates human-centered and responsible implementation of GenAI in education.

Most available evidence comes from international university settings and cannot be assumed to transfer to an island-state context, where access, teaching practice and assessment expectations may differ. The study therefore surveyed undergraduates at FEST, MNU to provide a baseline account of what students know about GenAI, how they use it, which tasks they find helpful and how they view its benefits and risks. The study does not test learning gains, causal effects, academic misconduct or independent-learning outcomes.

A. Study Objectives and Research Questions

The study addressed six research questions: (RQ1) What do undergraduate students know about selected GenAI capabilities and limitations? (RQ2) For which academic activities do they use GenAI? (RQ3) How helpful do students who provide ratings perceive GenAI to be for specific academic activities? (RQ4) What attitudes and perceived information or institutional guidance needs do students report concerning GenAI? (RQ5) Do the measured outcomes differ by year of study? (RQ6) What associations exist among knowledge, breadth of academic use, perceived helpfulness and individual attitude items? Analyses were exploratory. Degree-program comparisons initially proposed could not be performed because the response dataset lacked a usable degree-program variable.

II. LITERATURE REVIEW AND CONCEPTUAL POSITIONING

A. Knowledge and Academic Utilization

AI literacy means understanding what GenAI can and cannot do and evaluating its outputs, not merely being comfortable with a chatbot interface (Walter, 2024). Köhler and Hartig (2024), whose instrument motivated the present questionnaire, distinguished knowledge from practical use and from attitudes. Academic level, discipline and prior competence are associated with uptake and engagement (Delcker et al., 2024; Qu et al., 2024; Stöhr et al., 2024), and common academic applications include feedback, summaries, idea generation, drafting and problem explanation (Almassaad et al., 2024; Chan and Hu, 2023).

Knowledge is distinct from familiarity and confidence. A student may know how to enter prompts and obtain fluent explanations without realizing that a system can fabricate references, rely on outdated assumptions or give different answers to the same prompt. Walter (2024) places critical appraisal alongside prompt design in AI literacy, and Köhler and Hartig (2024) separate objective knowledge from reported use and attitudes; the five-item test used here follows that distinction. A short test samples only particular misconceptions, however. It cannot capture AI literacy, which also involves ethical judgement, source evaluation, practical prompting and knowledge of institutional rules.

Use and knowledge need not go together. Delcker et al. (2024) link AI competence to intended and reported educational use, but this does not show that exposure improves understanding. Because GenAI offers immediate, plausible answers, repeated use may continue without verification and leave misconceptions intact; conversely, students who understand its limitations may use it more selectively. The direction and strength of any association were therefore treated as an empirical question, and the number of academic tasks for which students use GenAI was compared with their accuracy on factual knowledge statements.

Utilization can be defined in several ways, including frequency of interaction, range of tools used and breadth of academic activities, and these are not interchangeable. Almassaad et al. (2024) and Chan and Hu (2023) describe a diverse set of educational applications, from brainstorming and writing support to explanations and research assistance. A student who relies heavily on one task could score lower on task breadth than one who occasionally uses GenAI for several. Individual activities are therefore reported, and the number of activities selected (utilization breadth) is treated as neither a measure of time spent nor of proficiency, dependency or academic success.

B. Perceived Value and Attitudes

Use and helpfulness are separate questions: students may use a tool without benefit, and a positive appraisal of one activity need not apply to others. Studies of student perceptions report convenience and individualized support alongside concerns about reliability, copyright, privacy and integrity (Chan and Hu, 2023; Daher and Hussein, 2024; Johnston et al., 2024). Positive expectations and risk recognition can therefore coexist in the same population, and trust, perceived importance and ethical or environmental concerns should not be assumed to reflect a single “attitude” dimension.

Perceived helpfulness is a student’s own judgement of whether a tool helped with an intended task; it does not measure learning gains or the quality of submitted work. Chan and Hu (2023) and Daher and Hussein (2024) describe students valuing convenience, responsiveness and support with explanations and writing, which may matter most where immediate feedback is scarce. Yet an answer can feel helpful because it is rapid, fluent or reassuring even when it is incomplete or inaccurate.

Academic activities also differ in kind. Asking for feedback on a paragraph one has written is not the same as asking for a section of an assignment to be generated; both may be rated useful, yet they raise different questions about learning ownership and acceptable assistance. Chan (2023) argues that institutions should clarify acceptable use and academic integrity through policy and education, and Johnston et al. (2024) show that students judge different uses differently. Task-level prevalence and helpfulness are therefore more useful for course guidance than a single global satisfaction rating. The survey did not ask whether students acknowledged AI assistance, checked generated content or submitted unmodified text, and it cannot be used to infer misconduct.

Attitudes toward GenAI are also not a single favorable-unfavorable continuum. Trust in factual reliability, awareness of privacy risks, copyright concerns and recognition of GenAI’s importance need not move together, and an informed user may value GenAI while doubting its reliability. Batista et al. (2024), Chan and Hu (2023) and UNESCO (2023) support treating these views as complementary rather than contradictory. Agreeing that misinformation or bias is possible is also not the same as being personally anxious about it. The eight attitude items were therefore analyzed individually unless measurement evidence supported a composite scale.

The literature on overreliance also distinguishes risk awareness from practice. Zhai et al. (2024) discuss possible cognitive consequences when users accept generated output uncritically. The survey cannot test these mechanisms, because it neither observed verification behavior nor measured critical thinking. The literature does suggest a practical implication: guidance should go beyond access to tools and include demonstrations of validation, attribution and data minimization. This is a recommendation drawn from prior research and the descriptive results, not a causal finding.

C. Student Heterogeneity and Context

Studies from other higher education systems report differences in GenAI use across fields and levels of study (Qu et al., 2024; Stöhr et al., 2024), but published evidence specific to Maldivian undergraduates is limited. A faculty-level survey can show what guidance students need, provided its limits are acknowledged: self-selection, unequal subgroup sizes and no direct assessment of learning outcomes.

Qu et al. (2024) identify differences in engagement across disciplines, and Stöhr et al. (2024) report variation by academic level and field. Assessment demands may shape practice, for example coding and technical explanation in one program and editing and summarizing in another, but institutional context, access, policy and norms can confound broad comparisons. The online export contained no usable degree-program data, so only differences by year of study were tested.

Year of study is an imperfect proxy for academic experience. Senior students may face more complex assignments, whereas new entrants may use GenAI for introductory explanations and drafting, and the pattern need not be linear: assessment types and rules and access to training may matter more than time at university. Small numbers in the highest year groups also limit precision, so omnibus differences by year need conservative interpretation, multiple-comparison control and attention to effect sizes. They do not show that progressing through university improves knowledge.

The Maldivian context matters to this study. Higher education in an island setting may be shaped by differences in digital access, academic support and institutional expectations, and UNESCO (2023) recommends human-centered guidance that attends to privacy, equity and meaningful educational use. Evidence from FEST undergraduates can inform locally situated training and

assessment communication without assuming that results from larger international samples apply directly. Equally, a volunteer sample from one faculty cannot be taken as representative of all MNU students or all Maldivian undergraduates.

This study therefore describes, in four domains, what students know about selected capabilities and limitations of GenAI, where they use it academically, whether users who rated particular tasks found them helpful, and how they judge its benefits and risks. It then explores differences by study year and associations among the measures. The framing follows Köhler and Hartig (2024), but their scale validation cannot be assumed to transfer to an adapted questionnaire with different response formats. The aim is a transparent institutional baseline, not replication of their latent-variable model.

III. METHODS

A. Design, Setting and Participants

A quantitative, non-experimental, cross-sectional online survey was conducted among adult full-time undergraduates at FEST, MNU. Of 100 submitted questionnaires, two respondents reported that they were not eligible full-time FEST degree undergraduates and were excluded, leaving 98 eligible submissions. All 98 were included in the primary analysis. The dataset contained 22 additional records with answer patterns identical to another eligible record; matching answers do not establish duplicate participation, and no reliable identifier was available to justify exclusion. A distinct-answer-pattern analysis (n=76) was reported only as a sensitivity check. Data were collected between 13 and 30 October 2026. Although the analytic sample is approximately 41% of an estimated 238 eligible students, this is estimated population coverage rather than a verified response rate, because an exact invitation denominator was unavailable.

B. Instrument and Operationalization

The questionnaire was adapted from Köhler and Hartig (2024) to cover multiple GenAI products. Background variables included age, gender and year of study. Items B1 and B3 asked whether respondents felt well informed about GenAI and whether the university should provide more guidance on effective and responsible use, respectively; agreement categories were summarized separately. Six true/false/do-not-know knowledge statements (C1–C6) were administered. Five (C1, C2, C4, C5 and C6) were coded correct = 1 and incorrect/do not know = 0 (total 0 – 5; answer key false, true, false, true, false). C3 was excluded from the descriptive score following exploratory item analysis but its item-level results are reported; this post hoc decision limits comparability with the original instrument. Utilization breadth was the number of ten activities (D1–D10) for which any affirmative use response was recorded (0–10), not a measure of frequency, skill or reliance.

The questionnaire design specified four joint use/value response categories (no/no intention; no/possible future use; yes/not helpful; yes/helpful). In the deployed online version, however, most activity responses were a simple yes or no (730 of 980 activity cells), followed by a separate five-point helpfulness question. The four-category perceived-value coding therefore could not be reconstructed consistently. Valid helpfulness ratings were analyzed by activity, and the mean of each respondent's available ratings was used only in exploratory comparisons. Nonuse and missing helpfulness ratings were not treated as "not helpful".

Eight attitude items (E1–E8) assessed perceived reliability, privacy, bias, copyright, energy use, technological importance, transparency and misinformation, using ordinal agreement responses. Because the items differed in content and direction, they were analyzed individually rather than as a single attitude score.

C. Statistical Analysis

Descriptive frequencies and percentages used item-specific valid denominators. Means and SDs summarize the five-item knowledge index and the ten-task count of academic activities. Kruskal–Wallis tests compared the four study-year groups; where an omnibus test was significant, Dunn pairwise comparisons used Holm adjustment. The eight attitude comparisons across study years were also Holm adjusted. Spearman rank correlations were calculated using pairwise complete observations. To address multiple testing, Holm adjustment was applied separately to the eight associations of each of the three core predictors (knowledge, number of academic activities and exploratory helpfulness) with E1–E8, and separately to two guidance families of 12 comparisons each (B1 and B3), each comparing the item with the other guidance item, the three core predictors and the eight attitude items. Families were based on conceptual research-question groupings rather than on statistical significance. Adjusted $p < .05$ was the significance threshold; raw p-values and sample sizes were retained for transparency. The complete 78-pair exploratory matrix is available as a supplementary analysis. No correction was applied across these distinct families, so inference remains exploratory.

Internal consistency was assessed using the Kuder-Richardson Formula 20 (KR-20) for the five binary knowledge items and Cronbach's alpha for the eight attitude items. The analysis yielded a KR-20 coefficient of .415 (n = 98) and a Cronbach's alpha coefficient of .376 for the attitude items (n = 97 complete cases). Both coefficients indicated low internal consistency, providing insufficient evidence to support unidimensional scales. Consequently, the knowledge score was treated as a descriptive index, while the attitude items were analyzed individually. All inferential analyses were considered exploratory. All statistical analyses were conducted using Python.

D. Ethics

The study was approved by the Maldives National University Ethics Committee (approval number RE/2026/C-13, 1 October 2026). Participation was voluntary and responses were anonymous; no names or student identifiers were collected.

IV. RESULTS

A. Participants

Of 98 eligible respondents, 64 were male (65.3%), 33 female (33.7%) and one did not report gender. Year-one students formed 53.1% of the sample; the distribution across years was unequal, with only nine students in year four or above.

B. GenAI Knowledge

Knowledge scores for the five retained items (range 0–5) had a mean of 3.76 (SD = 1.12) and median of 4 (IQR 3–4); 23 students (23.5%) answered all five correctly. Recognition of possible factual inaccuracies was highest (96.9%), while recognition that chatbots may provide different responses to the same question was lowest (54.1%). Correct-response rates for the other statements were 82.7% (mathematical solutions are not always correct), 73.5% (information is not necessarily updated daily) and 68.4% (live web searching is not automatic for all chatbots). Item C3 ("GenAI chatbots can generate responses that resemble human-written language") was answered false by 65 respondents (66.3%), true by 30 (30.6%) and "do not know" by three. Its correlation with the sum of the other five items was negative ($r = -.37$, $p < .001$). This pattern warrants checking item wording and

coding; it does not by itself establish why respondents answered as they did. C3 was omitted from the descriptive knowledge index, a decision made after examining responses. Given KR-20 of .42, the index should not be interpreted as a validated one-dimensional measure of AI-literacy.

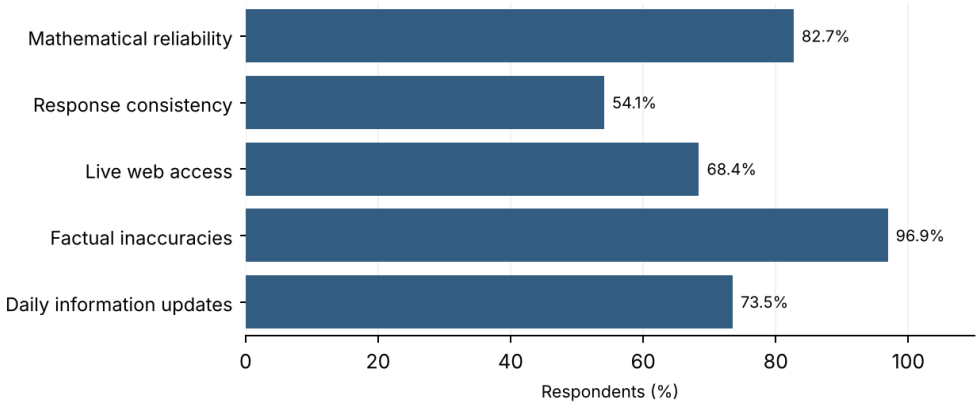


Figure 1: Correct answers across the five scored GenAI knowledge questions (n = 98).

C. GenAI Academic Utilization

Previous use of at least one GenAI product was reported by 97 respondents (99.0%). ChatGPT predominated (90; 91.8%), followed by Gemini (49; 50.0%), Copilot (32; 32.7%) and Claude (24; 24.5%). Respondents reported a mean of 5.04/10 distinct academic tasks (SD = 2.27), median 5 (IQR 4–6). The most common tasks were feedback on writing (83.7%), assignment outlines (78.6%), and content ideas (78.6%).

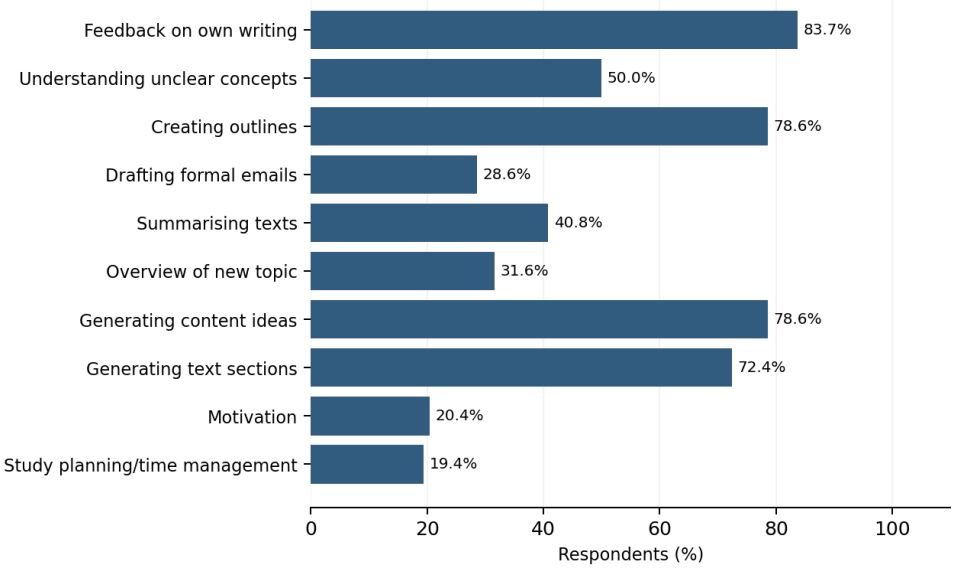


Figure 2. Academic activities for which students reported GenAI use (n = 98; multiple activities possible)

D. Task-Specific Perceived Helpfulness

Only 71 students provided at least one separate helpfulness rating. Conditional ratings were favorable for idea generation (60/62, 96.8% very or extremely helpful), concept explanation (27/28, 96.4%) and outlining (57/61, 93.4%). However, the number of ratings varied widely by activity, and some had very few (e.g. motivation, n = 5; study planning, n = 6). These results cannot be generalized to all 98 eligible respondents, so each percentage should be read with its denominator.

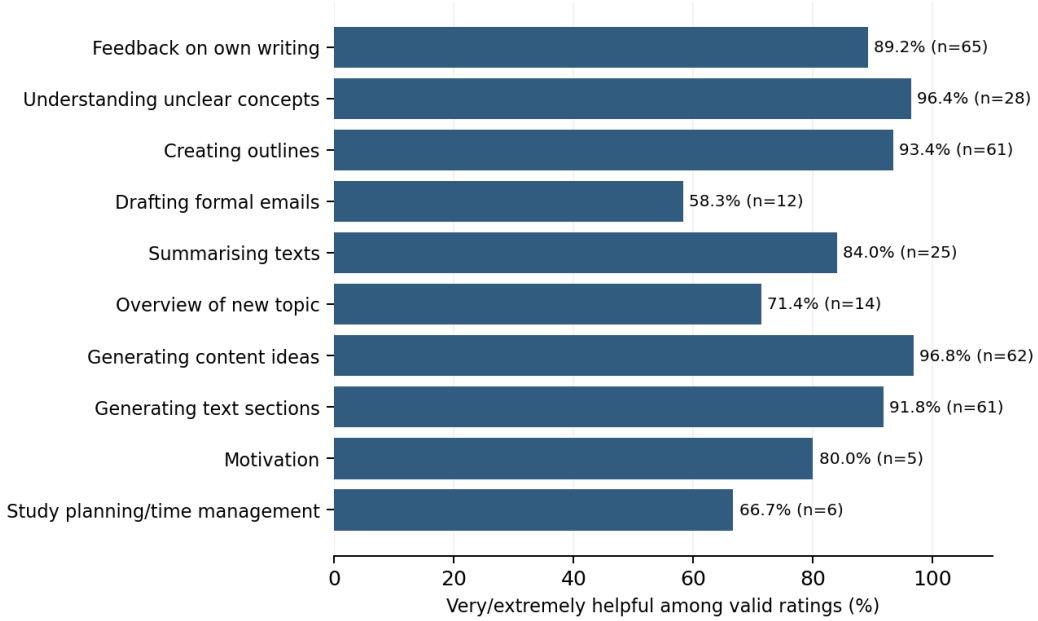


Figure 3. Very or extremely helpful responses among students who supplied a valid rating for each task (varying denominators shown)

E. GenAI Attitudes

Students generally recognized the significance of GenAI (84/98, 85.7%) and the possibility of misinformation (89/98, 90.8%), privacy risks (86/98, 87.8%) and bias (83/98, 84.7%). By contrast, only 35/97 (36.1%) agreed with the reliability/trust item, while 26/98 (26.5%) expressed energy-impact concern. These item-level contrasts indicate differentiated judgements rather than one uniform positive or negative orientation.

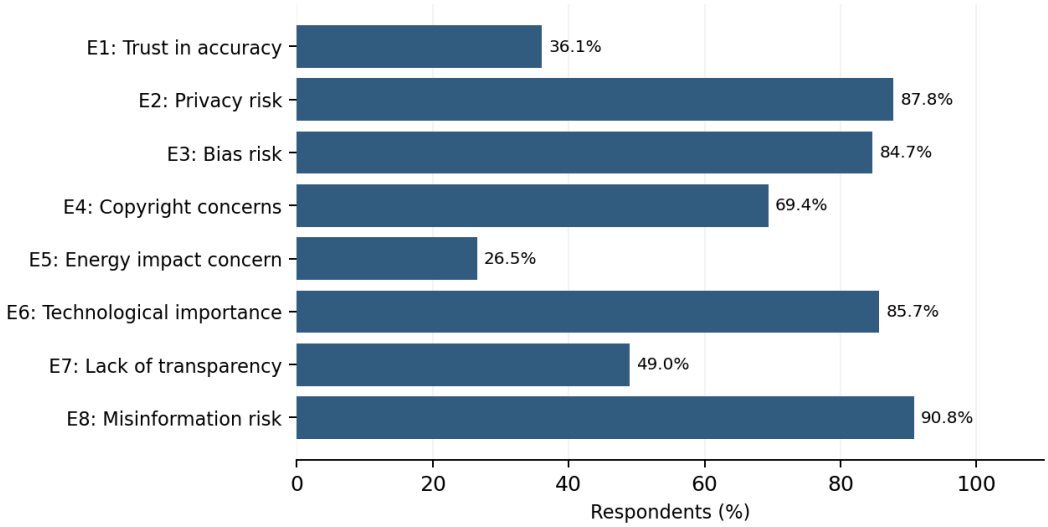


Figure 4. Agreement or strong agreement with GenAI attitude statements (n = 98 except accuracy trust, n = 97)

F. Perceived University Information and Guidance Needs

Item B1 asked whether students felt well informed about GenAI tools. Only 37/98 (37.8%) agreed or strongly agreed, 53/98 (54.1%) disagreed or strongly disagreed, and 8/98 (8.2%) were neutral. On B3, 91/98 (92.9%) agreed or strongly agreed that the university should provide more guidance on effective and responsible use of GenAI; 5/98 (5.1%) were neutral and 2/98 (2.0%) strongly disagreed. These items measured perceived information and support needs, not objectively assessed provision of university guidance.

Table 1. Students' perceived information and university guidance needs (n = 98)

Statement	Agree/strongly agree	Neutral	Disagree/strongly disagree
Feel well informed (B1)	37 (37.8%)	8 (8.2%)	53 (54.1%)
University should provide more guidance (B3)	91 (92.9%)	5 (5.1%)	2 (2.0%)

G. Differences by Year of Study

Knowledge differed overall across study years, $H(3) = 20.35$, $p < .001$, $\varepsilon^2 \approx .185$; mean (SD) knowledge was 3.33 (1.22) in year one, 4.33 (1.23) in year two, 4.12 (0.53) in year three and 4.44 (0.53) in year four or above. Dunn's pairwise tests with Holm adjustment showed that year-one students scored lower than students in year two (adjusted $p = .003$), year three (adjusted $p = .029$) and year four or above (adjusted $p = .015$); the later years did not differ from one another (adjusted $p \geq .535$). Utilization breadth did not differ significantly, $H(3) = 4.67$, $p = .197$, $\varepsilon^2 \approx .018$. Exploratory mean helpfulness did not differ significantly, $H(3) = 3.21$, $p = .360$, $\varepsilon^2 \approx .003$. Among eight separate attitudes, copyright concern (E4) was the only item that remained significant after Holm correction across items ($H(3) = 15.56$; raw $p \approx .001$; adjusted $p = .011$; $\varepsilon^2 \approx .134$). Agreement with the copyright item rose from

58% in year one to 100% in year four or above; Dunn's tests showed that year one differed from year three (adjusted p = .022) and from year four or above (adjusted p = .013), and year two from year four or above (adjusted p = .043). The small year-four-or-above group (n = 9) reduces precision.

Table 2. Omnibus differences by year of study (Kruskal–Wallis; p values unadjusted)

Outcome	Kruskal–Wallis H(3)	p	ε^2 (approx.)
Knowledge	20.35	< .001	.185
Utilization breadth	4.67	.197	.018
Mean helpfulness (exploratory)	3.21	.360	.003
Attitude E1	9.04	.029	.065
Attitude E2	4.45	.217	.015
Attitude E3	1.15	.766	.000
Attitude E4	15.56	.001	.134
Attitude E5	11.91	.008	.095
Attitude E6	1.12	.773	.000
Attitude E7	5.34	.148	.025
Attitude E8	5.26	.154	.024

H. Associations between Measured Variables

The three core comparisons were not significant: knowledge versus number of academic GenAI activities (ρ = −.184, p = .070; n = 98), knowledge versus mean perceived helpfulness (ρ = .145, p = .229; n = 71), and activity count versus helpfulness (ρ = .009, p = .938; n = 71). Following Holm adjustment within each predictor's eight attitude associations, knowledge was negatively associated with energy-impact concern (E5; ρ = −.400, adjusted p < .001). Greater utilization breadth was positively associated with accuracy trust (E1; ρ = .533) and perceived technological importance (E6; ρ = .406) and negatively associated with privacy concern (E2; ρ = −.408), copyright concern (E4; ρ = −.337), transparency concern (E7; ρ = −.273) and misinformation concern (E8; ρ = −.469); these six survived within-family Holm adjustment. All signs reflect the literal wording of the individual statements. Helpfulness was observed for only 71 students and is not fully comparable across tasks.

The eight attitudes did not form a validated scale, and conditional helpfulness ratings were missing for many respondents. Therefore, these results describe exploratory item-level associations, not correlations among four validated latent constructs. Holm-adjusted findings for the two additional institutional information families are reported separately below.

Table 3. Selected associations among survey variables (Spearman correlations; p values unadjusted)

Variable A	Variable B	n	ρ	p
Knowledge	Utilization breadth	98	−.184	.070
Knowledge	Helpfulness mean (exploratory)	71	.145	.229
Utilization breadth	Helpfulness mean (exploratory)	71	.009	.938
Utilization breadth	E1	97	.533	< .001
Utilization breadth	E2	98	−.408	< .001
Utilization breadth	E3	98	−.191	.060
Utilization breadth	E4	98	−.337	< .001
Utilization breadth	E5	98	−.051	.621
Utilization breadth	E6	98	.406	< .001
Utilization breadth	E7	98	−.273	.006
Utilization breadth	E8	98	−.469	< .001

I. University Information, Guidance Needs and Exploratory Correlations

In the B1 family (12 correlations), feeling informed was negatively related to knowledge (ρ = −.436, Holm-adjusted p < .001; n = 98) and to exploratory mean helpfulness (ρ = −.442, adjusted p = .001; n = 71), and strongly positively related to energy-impact concern (E5; ρ = .761, adjusted p < .001; n = 98). Because this last relationship was unusually large and the constructs are not validated scales, it warrants independent replication and careful examination of item interpretation. In the B3 family (12 correlations), wanting more university guidance was positively associated with mean helpfulness (ρ = .359, adjusted p = .021; n = 71), copyright concern (E4; ρ = .367, adjusted p = .002; n = 98), and transparency concern (E7; ρ = .288, adjusted p = .036; n = 98), and negatively associated with accuracy trust (E1; ρ = −.316, adjusted p = .018; n = 97). The two guidance items were not significantly associated after correction (ρ = −.251, adjusted p = .100; n = 98). Knowledge and number of academic activities were not significantly associated with wanting more guidance after adjustment.

Table 4. Significant exploratory correlations involving perceived institutional information and guidance needs, after Holm correction within separate B1 and B3 families

Item	Associated measure	n	Spearman ρ	Holm p
B1: Feel informed	Knowledge	98	−.436	< .001
B1: Feel informed	Mean helpfulness	71	−.442	.001
B1: Feel informed	E5 Energy-impact concern	98	.761	< .001

B3: Want guidance	Mean helpfulness	71	.359	.021
B3: Want guidance	E1 Accuracy trust	97	−.316	.018
B3: Want guidance	E4 Copyright concern	98	.367	.002
B3: Want guidance	E7 Transparency concern	98	.288	.036

V. DISCUSSION

A. Near-Universal Adoption Alongside Uneven Knowledge

Almost every respondent (99%) had used GenAI, so use is effectively universal in this sample. Knowledge, however, varied markedly by topic: nearly all students recognized that chatbots sometimes produce incorrect information (96.9%), but only just over half knew that the same question could produce different answers on different occasions (54.1%), and the other three items were answered correctly by between 68.4% and 82.7%. This gap between exposure and specific factual understanding is consistent with the distinction between use and knowledge drawn by Köhler and Hartig (2024) and with Walter's (2024) argument for AI literacy. The absence of a significant correlation between knowledge and utilization breadth does not mean that practice fails to build expertise, because breadth counts activities, not duration, proficiency, prompting, verification or learning. Alongside these domain-specific patterns, most respondents wanted additional university guidance (91/98, 92.9%), despite only 37/98 (37.8%) agreeing they felt informed. This gap is a perceived institutional information need, not proof that existing university services are absent or ineffective.

Köhler and Hartig (2024) examined separately measured knowledge, use, perceived use value and attitude constructs. Their measurement findings cannot be assumed to hold for an adapted faculty-level instrument. The five-item knowledge index had limited internal consistency (reported KR-20 = .42), and the additional item C3 showed an inverse item-rest association. Its exclusion should be interpreted cautiously because problems with coding, wording or construct coverage cannot be distinguished conclusively from these data alone. The clearer contribution is the item-level contrast between recognition of factual accuracy and weaker recognition of response variability. These findings justify targeted instruction on specific GenAI limitations, not claims about comprehensive AI literacy.

The near-universal use should also be interpreted in light of how the sample was recruited and measured. Students with stronger digital engagement may be more willing to join a voluntary online survey, and having ever used a tool is a low threshold compared with sustained academic use.

B. Writing Support and the Boundaries of Perceived Benefit

Students mainly reported using GenAI for writing feedback, outlining and idea generation, which resemble the applications described by Chan and Hu (2023) and Almassaad et al. (2024). This pattern is relevant to assignment design and to setting clear expectations for permissible assistance. It is not evidence that respondents plagiarized or that GenAI harmed their cognitive autonomy. Likewise, the high helpfulness ratings reflect perceived convenience and usefulness, not verified improvements in accuracy or performance.

The activities also differ between process-oriented support and product-oriented generation. Feedback on a student's own text may encourage revision, whereas generating whole sections could replace opportunities for independent drafting if used without reflection. The questionnaire did not establish the quality of that assistance or whether students verified or acknowledged the outputs, so the prevalence of drafting-related tasks should inform further inquiry and assessment guidance, not claims about integrity violations or diminished learning. Chan (2023) suggests that institutions describe permitted and prohibited use in task-specific rather than generic terms.

The helpfulness percentages are conditional on answering the follow-up question, and the denominators differed widely across activities. Students who did not answer may include nonusers as well as users who met survey-routing or response-format problems, so the high percentages cannot be extrapolated to all 98 eligible students. A future instrument should use a consistent two-stage design: first ask whether a task was used, then ask all users to rate its helpfulness, with explicit skip logic.

C. Valuing GenAI while Questioning Trustworthiness

High agreement with GenAI's technological importance coexisted with low endorsement of trust in factual accuracy and strong agreement about misinformation, privacy and bias. This pattern echoes the coexistence of perceived benefits and ethical worries described in Chan and Hu (2023) and Johnston et al. (2024). Risk responses need not be the inverse of acceptance: a student may use GenAI frequently while considering verification essential. The observed inverse associations between utilization breadth and several risk concerns are noteworthy, but may reflect selection effects, familiarity, differing response tendencies or other unmeasured variables rather than a reduction in caution caused by use.

Agreement that GenAI is important should not be equated with trust in its answers, and the pairing here is consistent with literature reporting benefits alongside perceived risks (Chan and Hu, 2023; Batista et al., 2024). Equally, risk awareness is not proof of safe practice: a respondent may agree that private information could be exposed and still enter it in a prompt. Future work could examine actual information-handling, verification and disclosure practices, subject to ethical safeguards.

Higher utilization breadth was associated with greater trust in accuracy and perceived technological importance and with lower endorsement of several risk statements. Because the attitude items do not form a validated scale, these are associations with beliefs, not with a general positive attitude. Multiple-testing correction reduces, but does not eliminate, the possibility of spurious findings; unmeasured third variables remain plausible; none of these associations shows what changes students' beliefs. Knowledge was also associated with lower concern about energy use (E5); this unexpected result may reflect familiarity with the technology or unmeasured differences between students and warrants replication.

D. Differences by Academic Year

The reported omnibus knowledge differences were followed by Holm-adjusted pairwise comparisons indicating lower scores in year one than in each of the later-year groups. No differences among the later-year groups were reported. These cross-sectional comparisons cannot establish that knowledge improves as students progress through university: curriculum, cohort, prior training and selection effects may contribute. The year-four-or-above subgroup was small (n = 9), and the knowledge index had limited internal consistency. Utilization breadth did not differ significantly across years. Copyright concern was the only attitude

item significant after adjustment in the primary analysis, but this result was not robust in the sensitivity analysis. Interpretations should therefore remain exploratory.

The year comparison is exploratory. A larger study could predefine a small number of theoretically meaningful comparisons, recruit more evenly across years and test whether differences persist after accounting for prior GenAI training and the types of assignments students receive.

E. Institutional Guidance and Practical Implications

The strongest actionable finding is that 91 of 98 respondents (92.9%) endorsed additional university guidance on the effective and responsible use of GenAI, while 53 (54.1%) disagreed that they felt well informed. FEST and MNU could therefore consider brief AI-literacy and academic-integrity sessions addressing output verification, inaccurate references, privacy, attribution, acceptable assignment assistance and task-specific examples. These are recommendations responding to perceived student needs; the survey did not evaluate availability, quality or effectiveness of existing institutional guidance. Subsequent evaluation could measure whether such provision improves understanding or responsible use.

The expanded exploratory correlations provide additional context for the strong demand for institutional guidance. Students who perceived greater usefulness in the rated activities also tended to want more university guidance, and specific concerns about copyright and transparency were associated with requests for guidance. These results do not show that such attitudes cause support needs or that current university provision is inadequate. Also, neither the five-item knowledge index nor utilization breadth was significantly associated with wanting guidance in the corrected B3 family. The high observed correlation between feeling informed and energy concern should be treated cautiously and checked in further studies.

VI. STRENGTHS AND LIMITATIONS

A. Strengths

The study provides timely, locally grounded evidence across four distinct areas (knowledge, use, helpfulness and attitudes) and reports item-level denominators, so missing data are visible rather than hidden.

B. Limitations

The analytical sample covered an estimated 41% of the approximately 238 eligible students, but the precise invitation denominator and therefore a verified recruitment response rate were unavailable and self-selection may affect representativeness. The sample came from one faculty; the study-year groups were unequal, and degree-program comparisons were unavailable. Data on tool use and perceptions were self-reported, and no direct learning outcomes or longitudinal changes were measured. The deployed activity or helpfulness questions differed from the planned four-category design, preventing reconstruction of the intended use or value scale. Only 71 of 98 respondents provided any helpfulness rating, with smaller activity-specific denominators. C3 was excluded following item analysis, and the retained five-item knowledge index had limited internal consistency (reported KR-20 = .42); the heterogeneous attitude items were not combined ($\alpha = .376$). Identical answer patterns were observed for 22 respondents, but such patterns do not establish duplicate participation. All eligible records were retained for the primary analysis. In the sensitivity analysis excluding these records ($n = 76$), the knowledge difference by study year remained significant ($p < .001$) and the knowledge-utilization association remained nonsignificant ($p = .115$), whereas several attitude findings changed. Because multiple analyses were exploratory and adjustment was within rather than across testing families, apparent associations require replication.

VII. CONCLUSION

Among participating FEST undergraduates, previous GenAI use was near-universal and concentrated on writing support, while accuracy on selected knowledge statements and attitudes toward reliability and risk varied. Knowledge differed by study year, but breadth of academic use did not; the two were not significantly associated. Most respondents (92.9%) wanted more university guidance on effective and responsible GenAI use, and over half (54.1%) did not feel well informed. These findings support targeted institutional information, transparent rules for academic assistance and AI-literacy education. As the sample was voluntary and drawn from one faculty, and the adapted measurement scales had limitations, results describe respondents rather than establish population prevalence, educational effects or causal relationships.

DECLARATIONS

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Author contributions: Both authors discussed and carried out all stages of the work together, including conceptualization, data collection, analysis and writing.
AI assistance disclosure: During the preparation of this manuscript, the authors used Google Gemini 1.5 Flash to assist in synthesizing key conceptual arguments and refining the structural flow and clarity of the discussion section. Following the use of this tool, the authors thoroughly reviewed, edited, and verified all generated content, and assume full accountability for the accuracy and integrity of the final published work.

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