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Generative artificial intelligence and academic outcomes of Philippine information technology students

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ABSTRACT

Generative artificial intelligence (AI) is increasingly embedded in higher education, yet evidence from Philippine computing programs remains limited. This study examined whether student characteristics and generative AI use patterns are associated with academic outcomes among Bachelor of Science in Information Technology (BSIT) undergraduates at a Philippine public university. Using a quantitative-dominant mixed-methods design, the study administered a descriptive–correlational survey to 60 randomly selected students and used short interviews and open-ended responses to contextualize the quantitative results. Descriptive statistics summarized participant characteristics and tool use, while multivariate tests examined associations with perceived academic benefits and self-reported academic performance. Most respondents reported frequent use and high familiarity and described benefits for engagement, idea development, and learning flexibility. However, students also reported distraction, overreliance, and occasional inaccuracies. Age, frequency of use, and familiarity were significantly associated with academic outcomes, whereas gender and year level were not. The findings indicate that generative AI can support student learning when institutions pair curricular integration with verification practices, ethical-use guidance, and assessment designs that preserve independent thinking.

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1. INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in higher education through learning analytics, adaptive systems, automated feedback, and student-facing assistants. Recent syntheses show rapid growth of AI-in-higher-education research and highlight both opportunities and persistent concerns about pedagogy, ethics, and equity [1], [2]. Since late 2022, generative AI—particularly large language models that can produce fluent text and code—has accelerated institutional interest because these systems can support common academic tasks at scale [3], [4].

Evidence suggests that conversational agents can support learning through immediate explanations, brainstorming, and scaffolding; however, effectiveness depends on how learners use these tools and how institutions design guidance and assessment [5]–[7]. In academic writing, for example, generative AI can improve drafts and language quality but may also shift students' cognitive effort toward editing rather than original composition [8]. As a result, AI literacy—including the ability to evaluate outputs, recognize limitations, and use AI ethically—should be treated as a core competence for higher and adult learners [9].

Alongside potential benefits, generative AI introduces practical and ethical challenges. Studies underscore concerns about misinformation, privacy, bias, and unequal access, which can affect learning outcomes and the credibility of assessment [10]. Higher education institutions are also revising academic integrity policies and assessment designs to address unacknowledged AI use, while still enabling constructive pedagogical applications [11]–[14].

Large-scale surveys show that students are already adopting generative AI broadly and are negotiating trade-offs between efficiency and trustworthiness [15], [16]. Yet empirical evidence remains uneven across disciplines and regions, and computing-related programs may face distinctive dynamics because students can use generative AI for programming, debugging, and problem solving [17]–[20]. In the Philippine context, published evidence on how generative AI use relates to undergraduate academic outcomes—especially among Bachelor of Science in Information Technology (BSIT) students—remains limited. Addressing this gap is important for designing internationally comparable guidance on responsible use in technology-intensive curricula.

This study addressed the scientific question of whether student characteristics and generative AI use patterns are associated with academic outcomes among BSIT students in a Philippine public university. Its specific novelty is not merely the Philippine setting, but the way it combines a quantitative test of demographic factors, frequency of use, and tool familiarity against a multidimensional academic-outcomes measure with qualitative explanations of why those patterns emerge in a computing-intensive program. Unlike studies that focus mainly on adoption intention or general student attitudes, this study examines whether actual use intensity and familiarity are differentially associated with perceived academic benefits and self-reported academic performance, then interprets those associations through students' explanatory accounts. The study therefore contributes institution-level evidence from an underrepresented context while also offering a mixed-method account of how generative AI becomes academically helpful, distracting, or unreliable in day-to-day BSIT learning tasks. The study was guided by the following questions:
- What are the patterns of generative AI use and familiarity among BSIT students? (RQ1).
- Which demographic and use-related factors are associated with academic outcomes? (RQ2).
- What benefits and concerns do students report regarding generative AI in their learning? (RQ3).

To strengthen the quantitative direction of analysis, the following hypotheses were also tested:
- Higher frequency of generative AI use is associated with more favorable academic outcomes (H1).
- Greater familiarity with generative AI tools is associated with more favorable academic outcomes (H2).
- Academic outcomes vary across age and year-level groups because students at different stages of study may engage with generative AI differently (H3).

Gender was examined as a control factor because prior findings remain mixed.

2. METHOD

2.1. Research design

This study employed a quantitative-dominant mixed-methods approach with an explanatory purpose, where quantitative results were prioritized and qualitative responses were used to contextualize and clarify observed patterns [21], [22]. Operationally, the study followed a sequential explanatory logic: the survey was administered and analyzed first, the preliminary quantitative results were then used to identify the issues needing explanation (for example, why frequency, age, and familiarity were related to academic outcomes, and why gender and year level were not), and short interviews plus open-ended responses were subsequently reviewed to elaborate those patterns. The primary phase used a descriptive-correlational survey to examine associations between student characteristics, generative AI use, and academic outcomes.

2.2. Participants and sampling

Participants were 60 BSIT students enrolled at Kalinga State University, Philippines, during the study period. The sampling frame included currently enrolled first- to fourth-year BSIT students, and respondents were selected through simple random sampling. Participation was voluntary, and only students who consented and completed the questionnaire were included in the analysis. Because the study was designed as an exploratory, institution-bounded mixed-methods inquiry rather than a population-estimation study, the sample size of 60 was treated as methodologically acceptable for screening directional associations and generating contextual explanations within one program [21], [22]. The modest n nonetheless requires cautious interpretation of inferential results and limits generalizability. Because the study focused on generating institution-specific evidence from one public university, the sample should be interpreted as exploratory and context-bound rather than broadly representative of all Philippine information technology students.

2.3. Instruments and measures

The survey instrument had four parts: i) demographic profile (gender, age group, and year level); ii) generative AI use (frequency of use); iii) familiarity with generative AI tools; and iv) academic outcomes, operationalized as perceived academic benefits (e.g., engagement, idea development, and learning flexibility) and self-reported academic performance. Items on use and perceived outcomes were organized as Likert-type statements. The measurement rationale was informed by recent studies of generative AI acceptance and use in higher education that emphasize awareness, trust, perceived usefulness, ease of use, and intention or actual use [23]–[26]. Because the instrument was used to generate rapid institution-level evidence, full psychometric validation and reliability estimation were not completed in the present dataset; thus, the measures are interpreted as exploratory indicators rather than standardized scales.

2.4. Data collection and ethics

Quantitative data were collected using a structured online questionnaire administered via Google Forms. A subset of respondents participated in short, semi-structured interviews and provided open-ended comments to elaborate on perceived benefits and concerns. Integration was conducted at two points of the analytic process: first, after the quantitative analysis, the researcher reviewed the qualitative responses specifically to explain statistically significant and non-significant quantitative patterns; second, the merged interpretation was written through side-by-side comparison of numerical trends and recurring qualitative themes in the Results and Discussion sections.

2.5. Data analysis

Quantitative data were summarized using descriptive statistics (frequency and percentage). Associations between student factors (gender, age, year level, frequency of use, and familiarity) and academic outcomes were examined using multivariate tests (e.g., Wilks' Lambda and Pillai's Trace) at a significance level of 0.05, implemented in IBM SPSS Statistics. Because academic outcomes combined perceived benefits and self-reported academic performance, the multivariate tests assessed associations with a multidimensional outcome rather than causal effects. Given the modest sample size, inferential findings are interpreted cautiously as exploratory directional evidence rather than population-level estimates. Qualitative data from interviews and open-ended responses were analyzed using reflexive thematic analysis to identify recurrent themes that explain or nuance the quantitative results [22]. To operationalize mixed-method integration, the qualitative codes were mapped against the quantitative findings as confirming, expanding, or cautionary evidence. This allowed the qualitative material to explain why certain factors appeared significant while also surfacing limits such as distraction, overreliance, and inaccuracy that the numerical results alone could not fully capture.

3. RESULTS AND DISCUSSION

3.1. Participant characteristics

The study involved 60 BSIT students. Gender distribution is summarized in Table 1, showing a higher proportion of female respondents (56.7%). Age distribution is presented in Table 2, with most respondents between 19 and 23 years old (91.7%). Table 3 summarizes year level, indicating that senior students comprised the largest group (48.3%).

Table 1. Gender distribution of respondents

Gender	Frequency	Percentage (%)
Male	26	43.3
Female	34	56.7
Total	60	100.0

Table 2. Age distribution of respondents

Age group (years)	Frequency	Percentage (%)
15–18	3	5.0
19–20	27	45.0
21–23	28	46.7
24 and above	2	3.3
Total	60	100.0

Table 3. Year level of respondents

Year level	Frequency	Percentage (%)
First year	7	11.7
Second year	5	8.3
Third year	19	31.7
Fourth year	29	48.3
Total	60	100.0

3.2. Generative AI use and familiarity

Table 4 presents how frequently respondents reported using generative AI tools for academic tasks. Nearly half of the respondents reported very frequent use (46.7%). Familiarity levels are shown in Table 5, where 65.0% reported being very familiar with generative AI tools.

Table 4. Frequency of generative AI use for academic tasks

Frequency of use	Frequency	Percentage (%)
Occasionally	10	16.7
Frequently	22	36.7
Very frequently	28	46.7
Total	60	100.0

Table 5. Familiarity with generative AI tools

Familiarity level	Frequency	Percentage (%)
Slightly familiar	3	5.0
Moderately familiar	18	30.0
Very familiar	39	65.0
Total	60	100.0

3.3. Factors associated with academic outcomes

Multivariate tests were used to examine whether demographic characteristics and use-related factors were associated with academic outcomes. As summarized in Table 6, age (p=0.003) and frequency of use (p=0.016) showed statistically significant associations with academic outcomes. Familiarity with generative AI also showed a significant association (p<0.001). Gender (p=0.425) and year level (p=0.244) were not significant.

Table 6. Multivariate analysis of factors associated with academic outcomes

Factor	Wilks' Lambda	p-value	Interpretation
Gender	—	0.425	Not significant
Age	0.195	0.003	Significant
Year level	—	0.244	Not significant
Frequency of use	0.349	0.016	Significant
Familiarity	—	<0.001	Significant

3.4. Qualitative summary of reported benefits and concerns

Open-ended survey responses and interviews indicated that students commonly used generative AI for "brainstorming", "clarifying concepts", and obtaining "quick examples or solutions". Respondents linked these uses to faster task completion and clearer explanations, which aligned with the positive quantitative pattern for more frequent and more familiar users. At the same time, students also warned about "distraction", "reduced independent problem solving", and "occasional inaccuracies", suggesting that perceived academic gains were conditional on verification and self-regulation.

3.5. Patterns of use in an information technology program

The high proportion of respondents reporting frequent or very frequent use, together with high self-reported familiarity, suggests that generative AI tools have become part of students' routine academic workflow. This pattern mirrors broader student adoption trends reported internationally [15], [16] and supports claims that generative conversational AI is rapidly being integrated into everyday learning practices [4]–[7]. In computing-related programs, the appeal is amplified because generative AI can provide code examples, debugging suggestions, and rapid explanations, which are aligned with recent research on programming-related uses of generative AI [17]–[20].

3.6. Interpreting significant predictors of academic outcomes

The central scientific question was whether demographic characteristics and generative AI use patterns are associated with academic outcomes in a Philippine BSIT context. The quantitative evidence suggests a selective association: age, frequency of use, and familiarity were significant, whereas gender and year level were not. Because the evidence combines multivariate results with students' qualitative accounts, the study does not show that generative AI automatically improves achievement; rather, it suggests that academically beneficial use is linked to how confidently and critically students engage with these tools. This interpretation is consistent with recent higher education studies showing that adoption is shaped not only by usefulness and ease of use, but also by trust, prior awareness, and learner readiness [23]–[26]. At the same time, the pattern should not be read as uniformly beneficial. This interpretation differs from more cautionary work showing that AI-supported writing can redistribute effort away from original composition [8] and from reviews warning that overreliance can weaken cognitive engagement [27]. It also refines broader syntheses suggesting that tool availability alone does not guarantee educational benefit, because gains depend on pedagogical framing and student verification practices [28]. For instructors, these results imply that a one-size-fits-all policy is unlikely to work; students may require differentiated guidance based on prior familiarity and their ability to verify outputs.

3.7. Practical and policy implications

Respondents described benefits such as faster task completion and clearer explanations, but they also raised concerns about distraction and inaccurate outputs. These findings matter beyond the study site because they suggest that responsible curricular integration, rather than blanket prohibition or unrestricted use, is the more defensible institutional response. Consistent with broader higher education work showing that AI can either support or undermine learning depending on whether it augments or substitutes student reasoning [27], [28], universities should treat verification, disclosure, and critical evaluation as teachable practices rather than assumed skills. This interpretation also adds nuance to more optimistic adoption studies by suggesting that positive academic outcomes are conditional rather than automatic [15], [16]. Recent work on AI literacy and students' ethical experiences with generative AI further indicates that students need structured guidance, not merely access, to use these tools well [29], [30]. At the institutional level, academic integrity policies are evolving to address unacknowledged AI use while enabling legitimate learning support [11]–[14]. For information technology programs, a balanced approach may include: i) explicit disclosure requirements for AI assistance; ii) assessment designs that value process, justification, and reflection; and iii) learning activities that require students to critique AI-generated outputs rather than accept them uncritically.

3.8. Addressing risks of overreliance

Concerns about reduced independent problem solving are consistent with literature warning that overreliance on AI dialogue systems can affect cognitive engagement when tools replace, rather than augment, student thinking [27]. To address this risk, educators can position generative AI as a scaffold for practice (e.g., generating alternative explanations or examples) and then require students to demonstrate understanding through original reasoning, debugging, or design choices. This is likely to be especially important in information technology education, where students may use AI for code generation, debugging, and troubleshooting. More broadly, prior work on AI in higher education suggests that the educational value of AI depends on pedagogical intent, assessment alignment, and ethical safeguards rather than tool availability alone [28]. Future work should test whether structured verification training, disclosure routines, and reflection-based assessments can reduce overreliance while preserving the efficiency benefits students value.

3.9. Limitations and future research

This study has several limitations. The sample was drawn from one institution and consisted of 60 respondents, which limits generalizability and does not support population-level claims. Measures relied primarily on self-report, including academic performance, and the questionnaire was used as an exploratory instrument without full psychometric validation or reported reliability coefficients in the present dataset. The cross-sectional design also prevents causal inference. Future studies should use multi-institutional samples of at least 100 participants, validate instruments formally, and incorporate objective academic indicators and longitudinal or quasi-experimental designs to test whether verification training, disclosure policies, or structured AI-assisted feedback improve outcomes in information technology programs.

4. CONCLUSION

This study addressed whether student characteristics and generative AI use patterns are associated with academic outcomes among Philippine BSIT undergraduates. The results answer RQ1 by showing that most respondents already use generative AI frequently and report high familiarity; answer RQ2 by showing that age, frequency of use, and familiarity—but not gender or year level—were significantly associated with academic outcomes; and answer RQ3 by showing that students perceive both academic benefits and risks, including faster task completion, clearer explanations, distraction, overreliance, and inaccuracies. Taken together, the evidence indicates that generative AI has educational value when its use is guided by AI literacy, verification routines, and assessment designs that preserve reasoning and accountability. The study's significance lies in providing context-specific evidence from a Philippine public university, although interpretation should remain cautious because of the small, single-institution, self-report sample and the exploratory measurement approach. Future research should expand the sample, strengthen instrument validation, and test intervention-based models for responsible AI integration in information technology education.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

Informed consent was obtained from all student respondents before participation in the survey, interviews, and open-ended responses. Participation was voluntary, and respondents were informed that their responses would be used only for research purposes and reported without personally identifying information.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [RUW], upon reasonable request. To safeguard the privacy of participating students, survey datasets are not publicly accessible.

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