

Generative AI in undergraduate learning: A cross-cultural study of U.S. and Albanian students

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Abstract

Generative artificial intelligence (AI) tools have rapidly become integrated into undergraduate academic life, raising important questions about how students use these technologies and how institutions should guide responsible use. This exploratory cross-sectional survey study examined generative AI use among 229 undergraduate students from three higher education institutions in the United States and Albania. The study investigated AI adoption, academic use cases, AI self-efficacy, prompting competency, governance awareness, perceptions of acceptable AI use, and learning-oriented versus substitution-oriented AI behaviors. Findings indicate that generative AI use is highly normalized, with most students reporting regular academic use and describing AI as useful for concept explanation, studying, brainstorming, summarization, and writing support. Although learning-oriented uses were most common, some students also reported substitution-oriented behaviors such as obtaining homework answers or generating assignment content, suggesting that student AI use exists on a continuum between learning support and academic outsourcing. Cross-cultural comparisons suggest that U.S. students reported more workflow-oriented and productivity-focused uses, while Albanian students relied more heavily on AI for conceptual explanation and tutorial-style support. These findings highlight the need for higher education institutions to strengthen AI literacy, develop students' prompting and evaluation skills, clarify expectations for acceptable use, and encourage reflective engagement with AI-supported learning.

Keywords: generative AI, AI literacy, student adoption, self-efficacy, academic integrity, cross-cultural comparison

Introduction

Generative AI has moved rapidly from novel technology to an ordinary part of students' academic routines. Undergraduate students can use conversational AI tools to summarize readings, brainstorm ideas, explain difficult concepts, revise writing, generate examples, and solve problems. These use cases create new opportunities for personalized academic support, but they also complicate long-standing assumptions about authorship, assessment, independent work, and academic integrity. For information systems educators, the issue is not only pedagogical. It is also a sociotechnical adoption problem in which students learn to use emerging systems, evaluate probabilistic output, interpret institutional expectations, and make judgments about ethical and appropriate use.

This study examines undergraduate students' reported use of generative AI for academic work across institutions in the United States and Albania. Rather than treating AI use as a simple yes-or-no behavior, the study distinguishes between frequency of use, the types of academic tasks supported by AI, students' judgments about acceptable use, and the degree to which students use AI reflectively to support learning rather than substitutionally to complete work. The study also examines AI self-efficacy, including students' perceived ability to ask useful questions and use AI productively for learning. This emphasis is important because students may use AI frequently without using it well, and students may also avoid useful AI-supported learning strategies if they lack confidence or guidance.

The cross-cultural dimension of the study is important because student AI use may be shaped by institutional context, access to guidance, educational norms, academic discipline, and exposure to AI tools. Students at different institutions may use the same technologies for different purposes, learn about AI through different formal and informal channels, and interpret acceptable use in diverse ways. By comparing responses from U.S. students at two New England business-focused institutions with students from an engineering-focused university in Albania, this study seeks to better understand how generative AI is being integrated into undergraduate learning and where institutions may need to strengthen AI literacy, assignment-level guidance, and responsible-use expectations.

Background and Literature Review

Generative AI has quickly moved from a novel technology to a tool that many students now encounter in their everyday academic work. Using tools such as ChatGPT, Claude, and Gemini, students summarize readings, brainstorm ideas, explain difficult concepts, revise writing, generate examples, and solve problems. While these tools create obvious opportunities for learning support, they also raise questions for faculty, administrators, and students about where assistance ends and inappropriate substitution begins. For information systems educators, this is not only an issue about classroom policy or academic integrity, but also one of adoption. Students are learning to use emerging technologies, often outside formal instruction, while also navigating evolving instructor expectations and institutional rules. As a result, student AI use is best understood as a sociotechnical issue shaped not only by technology, but also by factors such as student confidence, peer norms, course expectations, assignment design, and academic culture. This literature review considers seven areas that help frame student use of generative AI: its use in higher education, AI literacy, informal learning and adoption, AI self-efficacy, reflective versus substitution-oriented use, academic integrity, and cultural and institutional factors.

Generative AI in Higher Education

Research on artificial intelligence in higher education predates recent conversational AI tools and initially focused on systems such as intelligent tutoring, automated feedback, and learning analytics (Zawacki-Richter et al., 2019). The recent growth of generative AI, expanded both the scale and visibility of student use, shifting their access from institutionally provided systems to direct interaction with tools of their choice for use in their academic work.

While generative AI tools can support academic tasks including writing, explanation, feedback, and personalized learning, their use also raises concerns about accuracy, bias, overreliance, and assessment (Kasneci et al., 2023). Chan and Hu (2023) similarly found that students recognized potential benefits such as writing assistance, idea generation, and personalized support, but also raised concerns about reliability, privacy, and academic integrity. Research in information systems education highlights a gap between student and faculty perspectives, with students often emphasizing convenience and learning support while faculty focus more on ethics and academic integrity (Sah et al., 2025). These differences suggest that student

AI use should be understood in terms of how students are using AI and how they interpret appropriate boundaries, rather than as simply acceptable or inappropriate behavior.

AI Literacy as an Educational Outcome

AI literacy provides a useful lens to examine student use of generative AI because it distinguishes access from capability. A student may frequently use AI tools but still lack the ability to evaluate accuracy, bias, or appropriateness of AI-generated responses. Long and Magerko (2020) define AI literacy as the competencies needed to critically evaluate, communicate, and collaborate with AI, and use AI effectively in everyday life and work.

This distinction is especially important in higher education. Students may know that AI can produce answers, but not how to formulate effective prompts, verify outputs, recognize hallucinations, or determine whether AI assistance is appropriate. AI literacy extends beyond technical knowledge to include academic habits and good judgment. Recent work in information systems education reinforces this idea. Daniels (2025) separates AI engagement, the extent to which people seek information about AI and use AI tools, from AI literacy, or the knowledge and skills needed to use it appropriately. Frequent use does not necessarily indicate AI literacy; transparent use for learning may be a better indicator. AI literacy combines skills and habits including asking productive questions, evaluating responses, checking accuracy, and using AI to support understanding rather than simply completing tasks.

Student Adoption and Informal Learning

Technology adoption theory helps explain the rapid spread of generative AI use among students. Traditional adoption models emphasize perceived usefulness and ease of use (Davis, 1989), while the Unified Theory of Acceptance and Use of Technology (UTAUT) includes factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). In practice, students adopt AI because it saves time, clarifies difficult concepts, and improves writing, or because their classmates use it.

Recent information systems research applies these models to academic settings. Patterson et al. (2024), using a UTAUT perspective, found that productivity gains, mentor perspective, peer usage, and breadth of tasks were associated with undergraduate generative AI adoption. Rruplli et al. (2024), using the Value-Based Adoption Model, found that students weighed perceived benefits such as usefulness and enjoyment against sacrifices such as technical challenges, errors, and cost. These studies suggest that adoption reflects practical judgments about whether AI helps students work more efficiently or effectively. Similarly, Funda and Cilliers (2025) found that adoption depends on perceived usability and alignment with academic tasks. Longitudinal evidence from Frydenberg, Mentzer, and Patterson (2026) also shows growth in awareness and use of AI across first-year students during the first three semesters following its widespread introduction.

Because generative AI is widely available, students often learn to use these tools through informal learning channels such as classmates, social media, and experimentation. This can lead to effective but incomplete practice, where students adopt efficient strategies without necessarily understanding academic expectations, verification practices, or appropriate boundaries for use.

AI Self-Efficacy

Self-efficacy provides a useful lens for understanding how students use generative AI. Bandura (1997) defines self-efficacy as individuals' beliefs about their capability to organize and execute the actions required to achieve desired outcomes. In education, self-efficacy influences whether students begin tasks, persist through challenges, try alternative strategies, and regulate their learning. Applied to generative AI,

AI self-efficacy refers to students' confidence in using AI tools effectively for academic purposes. This includes asking productive questions, refining prompts, evaluating outputs, and applying information appropriately. Students with access to the same tool may use it in vastly different ways. One may rely on it for direct answers while another uses it for explanations, feedback, practice, or preparing for tests.

Research suggests that AI self-efficacy is associated with students' acceptance of generative AI. Zhang and Yu (2025) found that higher generative AI self-efficacy was associated with greater acceptance, partly through trust and perceived risk. This distinction suggests self-efficacy concerns confidence in using AI, while trust concerns students' beliefs around its reliability.

AI self-efficacy is also connected to broader AI literacy and student readiness. Bewersdorff et al. (2025) found relationships among AI use, attitudes, interest, AI literacy, and self-efficacy, while Kong et al. (2025) noted the role of AI in motivating learning. North and Riskas (2025) found that coursework incorporating progressive generative AI tasks can strengthen AI self-efficacy and improve performance.

At the same time, higher AI self-efficacy is not always a positive outcome. Confidence may support using AI for learning but may also result in over-reliance on answer generation if course expectations are unclear. The key issue is that AI self-efficacy supports learning or simply generates answers.

Learning Support, Cognitive Engagement, and Reflective Use

A recurring challenge in the literature is distinguishing learning-oriented use of generative AI from substitution of student work. Generative AI can support learning when students use it for explanations, examples, feedback, practice questions, or alternative solutions. These uses can resemble tutoring or scaffolding when students remain cognitively engaged. However, the same tools can also reduce learning used to produce final answers, complete assignments, or avoid difficult thinking.

This distinction aligns with self-regulated learning. Zimmerman (2002) describes self-regulated learners as students who plan, monitor, and evaluate their learning. Students who use AI for explanations, self-testing, or feedback use AI as a tool for metacognitive monitoring while those who rely on it to obtain answers may bypass the cognitive work required to complete their assignments. As a result, frequency of AI use alone is an incomplete measure. Students who use AI regularly for practice or understanding are engaging differently from a student who regularly uses it to complete an assignment. Both students may be frequent users, but the educational meaning of their use is quite different.

Many student uses of AI fall into gray areas between clearly acceptable support and clearly unacceptable substitution. Asking AI to explain a concept is different from asking AI to complete an assignment, yet both uses may occur in the same study session. White et al. (2024) emphasize that students' perceptions, including uncertainty about rules and expectations, can shape whether they use AI appropriately, openly, or covertly. For this reason, research should distinguish between learning-oriented uses, such as explanation, feedback, and practice, and substitution-oriented uses, such as producing answers or assignments. Without this distinction, studies risk misrepresenting the educational significance of AI use by treating all use as equivalent.

Academic Integrity and Responsible Use

Academic integrity remains a central concern in discussions of generative AI in higher education. Cotton et al. (2024) argue that tools such as ChatGPT create opportunities for student learning but also complicate authorship, plagiarism, assessment design, and detection. The academic integrity issue extends beyond "getting caught" to understanding permitted use and preserving the connection between assessment and learning. Responsible use requires more than a general warning against cheating. UNESCO's guidance

emphasizes human-centered use, capacity building, and attention to risks such as bias, privacy, and inequitable access (Miao & Holmes, 2023). In the classroom, this suggests that students need clear expectations at the assignment level. A broad institutional statement may be helpful, but it is unlikely to resolve the everyday decisions students face when deciding whether AI can be used for brainstorming, editing, studying, problem solving, or drafting.

While many institutions have reacted to generative AI with policies driven by a “plagiarism panic” and a reliance on software to detect AI usage, researchers suggest that a more fundamental shift in thinking about AI use is necessary. Hamman and Iyamu (2025) argue that instead of considering generative AI as a threat, institutions must develop new rules for acceptable use of AI that treats prompt engineering as a transparent pedagogical strategy that promotes critical thinking and emphasizes the role of the human as influential on the generation of AI content, ensuring students remain accountable and critically engaged authors. This issue is particularly relevant for information systems education. Courses should distinguish prohibited substitution from permitted learning support, while preparing students to use AI responsibly as professionals.

Cultural and Institutional Context

Student AI use is shaped by both technology access and educational context. Cultural and institutional factors influence prior exposure, language needs, assessment traditions, faculty expectations, academic integrity norms, and access to digital resources. For example, students using AI in a second language may depend on AI for translation, explanation, and writing support. Students whose institutions have explicit AI guidance may also interpret acceptable use differently from students relying primarily on peers or social media.

Comparative research highlights the importance of context. Mecaj (2023) found that Albanian students frequently used AI tools for solving exams and quickly finding information, while more institutionally mature systems in Germany showed stronger AI integration frameworks and policy discussions. Differences in educational policy, digital literacy, infrastructure, and institutional readiness influence how often students use AI and how they integrate it into their academic practices. In some contexts, AI is viewed primarily as a tool for immediate support rather than for reflective learning and long-term skill development.

Institutional responses also appear to vary. In the U.S., discussions on acceptable use, and academic integrity, emerged rapidly after the release of conversational AI tools. In contrast, some institutions remain at earlier stages of adaptation, where policies and practices often depend more on individual instructors. These differences not only influence how frequently students use AI tools, but also how they understand acceptable use. Effective use of generative AI depends not only on access to technology, but also on AI literacy and prompt engineering (Sah et al., 2025).

Summary and Research Gap

Prior research shows that students are rapidly adopting generative AI and that AI literacy, academic integrity, self-efficacy, and institutional context shape this adoption. Less is known about how these factors intersect across cultural settings and whether frequent use reflects reflective learning support or substitution-oriented use. This study addresses that gap by comparing undergraduate students in the United States and Albania across frequency of use, academic use cases, AI self-efficacy, acceptability judgments, and learning-oriented versus risk-prone behaviors.

This study contributes to the growing literature on generative AI in higher education by examining not only how often students use AI, but how they use it and how they perceive its role in learning. By comparing students from institutions in the United States and Albania, the study provides insight into how educational context shapes AI-supported learning practices. The findings also highlight the importance of distinguishing between learning-oriented and substitution-oriented AI use, offering a more nuanced understanding of student engagement with generative AI.

This leads to the following research questions:

- RQ1: How frequently do undergraduate students report using generative AI tools for school-related work?
- RQ2: What academic tasks do students report using generative AI to support most often?
- RQ3: To what extent do students report reflective, learning-oriented AI use versus substitution-oriented or risk-prone AI use?
- RQ4: How do students perceive the boundaries between acceptable AI-supported learning and inappropriate academic substitution?
- RQ5: How do students report AI self-efficacy in relation to academic AI use?
- RQ6: How do patterns of AI use, perceived learning value, AI self-efficacy, and perceived boundaries differ between the U.S. and Albanian student samples?

Methodology

This study employed a cross-sectional survey design to examine undergraduate students' use of generative AI tools in academic settings, with particular attention to AI adoption, AI literacy, self-efficacy, governance awareness, prompt engineering competency, and differences across cultural and institutional contexts. The methodological design was developed to align directly with the study's research questions concerning frequency of AI use, learning-oriented versus substitution-oriented behavior, perceptions of acceptable AI usage, AI self-efficacy, and cross-cultural differences between student populations in the United States and Albania.

A cross-cultural comparative approach was adopted involving undergraduate students from <redacted> and <redacted> in the United States, as well as <redacted> in Albania. This design enabled the examination of how differences in institutional environment, educational practices, governance structures, and academic disciplines may shape students' patterns of generative AI adoption, usage behaviors, and perceptions of appropriate and responsible academic use.

Survey Instrument

The survey instrument was originally developed as part of a broader effort to better understand how undergraduate students are using and thinking about artificial intelligence in higher education environments. Following its initial development, the questionnaire was distributed to undergraduate students at two U.S. universities and one university in Albania to support cross-cultural comparison and exploratory institutional analysis. The questionnaire included items designed to capture demographic characteristics, educational background, AI adoption behavior, AI literacy, governance awareness, and perceptions regarding acceptable AI use in academic settings. Students were asked to report their year of study, institution, and academic major or field of study.

Additional survey items examined how students first learned about AI tools for academic work, including classmates, social media, instructors, workshops, or self-directed experimentation. Students were also asked

to identify the types of academic activities for which they believed AI could be useful, including explaining concepts, summarizing readings, generating practice questions, improving writing clarity, and generating complete assignment answers. Several items specifically focused on AI self-efficacy and prompt engineering competency. These questions assessed students' confidence in asking effective questions, obtaining useful AI-generated explanations, and using AI tools in ways that support learning rather than simply generating answers. The questionnaire also included items examining students' understanding of institutional or classroom rules governing AI use in assignments.

Sampling and Data Collection

The sampling frame consisted of currently enrolled undergraduate students from the participating institutions. Participation was voluntary, and all responses remained anonymous throughout the data collection and analysis process to encourage candid reporting of AI-related behaviors and attitudes. The questionnaire remained active for one week across all participating institutions.

A total of 229 undergraduate students participated in the study. The sample included 131 students (57.2%) from two institutions in the United States and 98 students (42.8%) from one institution in Albania. Participants represented multiple academic years and disciplinary backgrounds, including business, STEM, and social science fields. Table below summarizes the characteristics of the study sample.

Table 1. Sample Characteristics and academic-field composition by country

Country	STEM	Business	Social/Other
Albania (n = 98)	94 (95.9%)	2 (2.0%)	2 (2.0%)
United States (n = 131)	7 (5.3%)	92 (70.2%)	32 (24.4%)
Total (N = 229)	101 (44.1%)	94 (41.0%)	34 (14.8%)

Measures

The study used exploratory measures aligned with the research questions. Frequency of AI use was treated as an ordinal item, perceived understanding was treated as a categorical item, and academic-field category was treated as nominal. Multi-response behavior items were coded as selected/not selected for each response option.

The learning-oriented versus substitution-oriented distinction served as an analytical lens, not as a validated latent construct. Learning-oriented items included explaining concepts, step-by-step support, brainstorming, summarizing, editing, and study-guide creation. Substitution-oriented items included getting homework answers and writing parts of assignments. Checklist reliability was examined only as a sensitivity check, with KR-20/Cronbach's alpha values ranging from .557 to .672 across exploratory item groups. Academic major or field of study was included as a nominal contextual variable to examine whether disciplinary composition was associated with differences in AI-use frequency or selected academic-use patterns.

Data Analysis

Analyses combined descriptive statistics with inferential tests. Country comparisons for nominal variables used chi-square tests with Cramer's V as an effect-size estimate. For the ordinal frequency item, a Mann-Whitney U test was used with r as the effect-size estimate.

For multi-response items, each response option was coded as a binary indicator and compared by country using chi-square tests. Reported p -values are interpreted cautiously because the study is exploratory and because country, institution, and academic field are strongly confounded in the sample.

A country-only supplementary odds-ratio analysis was computed for high-frequency use (Always/Often versus lower frequency). A multivariable logistic regression including country and academic field was not retained because sparse cells and the strong country-by-discipline imbalance would make adjusted estimates unstable. Spearman's rho was retained only as a sensitivity check for the coded academic-field variable; because academic field is nominal, crosstabulation and chi-square results are treated as the primary subgroup evidence.

Results and Findings

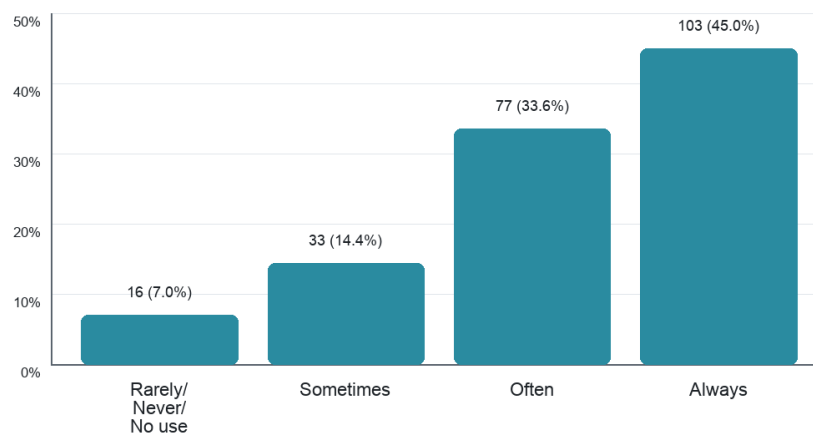
RQ1: Frequency of Generative AI Use

Reported AI use was common in the analytic sample. When the lowest-use categories were collapsed for stable comparison, 103 respondents (45.0%) reported Always using AI for school-related work, 77 (33.6%) reported Often, 33 (14.4%) reported Sometimes, and 16 (7.0%) reported Rarely, Never, or no AI use.

The frequency distribution differed by country/institutional group, chi-square(3) = 12.70, $p = .005$, Cramer's $V = .235$. The ordinal Mann-Whitney U comparison was not statistically significant, $U = 6846.0$, $z = 0.92$, $p = .355$, $r = .061$, indicating that the nominal distributional difference should be interpreted as modest and category-specific rather than as a broad ordinal shift.

Most respondents reported that AI had improved their understanding of course material ($n = 197$, 86.0%). This perceived-understanding item differed modestly by country/institutional group, chi-square(2) = 6.83, $p = .033$, Cramer's $V = .173$, with yes responses more common in the U.S. subsample (90.8%) than in the Albanian subsample (79.6%). Figure 1 summarizes the overall frequency distribution.

Reported frequency of generative AI use for school-related work

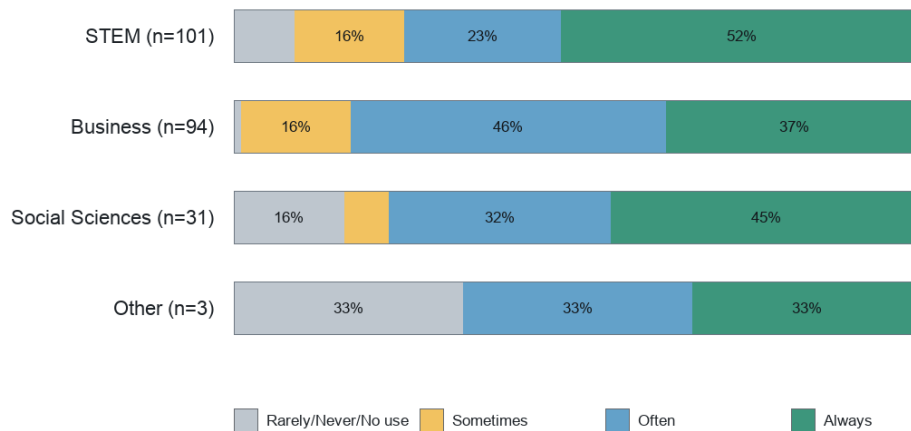


Note. Categories collapse 'I don't use AI,' 'Never,' and 'Rarely' for stable country comparisons.

Figure 1. Reported frequency of generative AI use for school-related work.

Academic-field comparisons also showed visible variation, but these results should not be separated from sample composition because STEM students were concentrated in the Albanian sample and Business/Social Science students were concentrated in the U.S. sample.

Frequency distribution by academic field



Note. The Other category is very small and should not be interpreted separately.

Figure 2. School-related AI-use frequency by academic field.

Table 2 reports the country/institutional comparison for school-related AI-use frequency using the collapsed categories used in the inferential test.

Table 2. Frequency of AI use for school-related work by country/institutional group

Country	n	Rarely/Never/No use	Sometimes	Often	Always
Albania	98	10 (10.2%)	15 (15.3%)	21 (21.4%)	52 (53.1%)
United States	131	6 (4.6%)	18 (13.7%)	56 (42.7%)	51 (38.9%)
Total	229	16 (7.0%)	33 (14.4%)	77 (33.6%)	103 (45.0%)

RQ2: Academic Tasks Supported by Generative AI

The multi-response academic-use item showed that learning-support uses were selected more often than explicitly substitution-oriented uses. The most common reported uses were understanding a topic (76.4%), step-by-step explanations (54.1%), summarizing notes/readings (48.9%), and brainstorming ideas (48.5%). Several learning-support items differed by country/institutional group, especially brainstorming, summarizing, editing, and study-guide creation. These differences likely reflect a mixture of institutional setting, assignment type, and disciplinary composition rather than national context alone. Substitution-oriented reported uses were present but less common: 23.1% selected getting answers to homework questions and 14.8% selected writing parts of assignments. Neither substitution-oriented item differed significantly by country/institutional group.

Table 3. Reported academic AI uses by orientation and country/institutional group

Reported use item	Total	Country comparison
Learning: Understanding a topic I don't get	175 (76.4%)	Albania 65.3%; US 84.7%; chi-square = 11.74, $p < .001$, $V = 0.226$
Learning: Getting step-by-step explanations	124 (54.1%)	Albania 52.0%; US 55.7%; chi-square = 0.31, $p = 0.580$, $V = 0.037$
Learning: Brainstorming ideas	111 (48.5%)	Albania 18.4%; US 71.0%; chi-square = 62.16, $p < .001$, $V = 0.521$
Learning: Summarizing notes or readings	112 (48.9%)	Albania 29.6%; US 63.4%; chi-square = 25.58, $p < .001$, $V = 0.334$
Learning: Editing or improving my writing	69 (30.1%)	Albania 19.4%; US 38.2%; chi-square = 9.39, $p = 0.002$, $V = 0.203$
Learning: Creating study guides or flashcards	73 (31.9%)	Albania 15.3%; US 44.3%; chi-square = 21.66, $p < .001$, $V = 0.308$
Substitution: Getting answers to homework questions	53 (23.1%)	Albania 19.4%; US 26.0%; chi-square = 1.36, $p = 0.244$, $V = 0.077$
Substitution: Writing parts of assignments for me	34 (14.8%)	Albania 17.3%; US 13.0%; chi-square = 0.85, $p = 0.357$, $V = 0.061$

RQ3: Learning-Oriented versus Substitution-Oriented AI Use

The learning-versus-substitution framework was operationalized as a coding procedure applied to selected checklist items, not as a validated psychometric construct. A respondent was classified as selecting learning-oriented behavior if any learning-support item was chosen and as selecting substitution-oriented behavior if any answer-generation or assignment-writing item was chosen.

Using this coding procedure, 218 respondents (95.2%) selected at least one learning-oriented reported-use item, while 63 respondents (27.5%) selected at least one substitution-oriented reported-use item. Fifty-nine respondents (25.8%) selected both learning- and substitution-oriented behaviors, suggesting that many students combine tutorial/support uses with at least occasional academically risky uses. Country/institutional comparisons for these broad classifications were not statistically significant: any learning-oriented use, chi-square(1) = 0.65, $p = .419$, $V = .053$; any substitution-oriented use, chi-square(1) = 0.00, $p = .991$, $V = .001$. Accordingly, the revised interpretation emphasizes coexistence rather than a simple division between learning users and substitution users.

RQ4: Perceived Boundaries and Rule Clarity

Students generally supported AI uses associated with learning support and academic assistance. The most Students more frequently selected learning-support practices as acceptable or appropriate than substitution-oriented practices. Explaining a concept in simpler terms (71.2%) and helping study for a test (65.5%) were the most frequently selected boundary items, while solving homework problems (18.8%) and writing an assignment from scratch (16.6%) were less frequently selected.

Table 4. Perceived acceptable AI-supported practices by orientation and country/institutional group

Boundary item	Total	Country comparison
Learning support: Generating ideas before I start writing	114 (49.8%)	Albania 29.6%; US 64.9%; chi-square = 27.93, $p < .001$, $V = 0.349$
Learning support: Checking grammar and clarity	118 (51.5%)	Albania 30.6%; US 67.2%; chi-square = 30.01, $p < .001$, $V = 0.362$

Boundary item	Total	Country comparison
Learning support: Explaining a concept in simpler terms	163 (71.2%)	Albania 52.0%; US 85.5%; chi-square = 30.59, $p < .001$, $V = 0.365$
Learning support: Helping study for a test	150 (65.5%)	Albania 52.0%; US 75.6%; chi-square = 13.74, $p < .001$, $V = 0.245$
Substitution: Solving homework problems	43 (18.8%)	Albania 19.4%; US 18.3%; chi-square = 0.04, $p = 0.838$, $V = 0.014$
Substitution: Writing an assignment from scratch	38 (16.6%)	Albania 18.4%; US 15.3%; chi-square = 0.39, $p = 0.533$, $V = 0.041$

The analytic dataset did not include a separately labeled institutional-policy clarity item. Therefore, governance awareness is discussed through these boundary-perception items and through the limitations of the available data rather than reported as a direct governance-clarity scale.

RQ5: AI Self-Efficacy and High-Frequency Use

The attached analytic file did not contain the complete multi-item AI self-efficacy scale described in the earlier draft, so the revised analysis does not present unsupported self-efficacy percentages. Instead, frequency of use and perceived improvement in understanding are reported directly from the available data. A supplementary high-frequency comparison (Always/Often versus lower frequency) found that 78.6% of the full sample reported high-frequency academic AI use. The U.S. subsample had higher odds of high-frequency use than the Albanian subsample, but the difference was not statistically significant, $OR = 1.53$, 95% CI [0.81, 2.88], $p = .191$.

The prior null Spearman-style result is interpreted cautiously because the academic-field code is nominal and country/institution is strongly confounded with discipline. As a sensitivity check, the association between coded academic field and frequency score was weak and non-significant, $\rho = -.065$, $p = .327$. This weak association is substantively plausible: generative AI confidence and routine use may now be widespread across disciplines because students encounter the same public AI tools, peer norms, and assignment pressures across courses. It should not be read as evidence that disciplinary context is irrelevant. Together, the RQ5 results suggest that future work should measure AI self-efficacy with a validated multi-item scale and examine whether confidence predicts learning-oriented use after accounting for institutional setting and academic discipline.

RQ6: U.S.-Albania Differences in AI Use and Perceptions

Country/institutional comparisons showed statistically significant differences in the frequency distribution and in several learning-support task selections. However, academic field and country were strongly associated, $\chi^2(3) = 191.67$, $p < .001$, Cramer's $V = .915$. These results therefore cannot be attributed to country alone. The most defensible interpretation is that reported AI use varies across a combined national, institutional, and disciplinary context. This exploratory pattern warrants follow-up research using samples that allow country, institution, and discipline to be modeled separately.

Implications for Research/Practice

The findings suggest that generative AI is already embedded in undergraduate academic practice, but its educational meaning depends on how students use it and how clearly institutions define acceptable support. Governance is especially important because students selected learning-support practices far more often than substitution-oriented practices, yet a meaningful minority still reported homework-answer or assignment-writing uses. Clear institutional and assignment-level guidance can help students distinguish explanation, feedback, study support, and brainstorming from outsourcing assessed work.

The country/institutional comparisons suggest that governance discussions should be localized. Differences in selected learning-support practices may reflect disciplinary work patterns and institutional expectations as much as national context. The weak Spearman sensitivity result also supports a cautious interpretation: AI confidence and routine AI exposure may be becoming common across academic fields, even when the specific tasks students use AI for differ by course type and assessment design.

AI literacy instruction should therefore include prompt design, verification of AI-generated content, source evaluation, disclosure norms, and reflective decisions about when AI supports learning and when it substitutes for learning. Faculty development is also needed. Instructors require practical guidance for communicating permitted uses, designing assessments that reward process and judgment, and responding consistently when AI use crosses course-defined boundaries. Future research should use balanced samples across countries, institutions, and disciplines; include direct policy-clarity items; and test validated AI self-efficacy and AI-literacy scales.

Limitations

Several limitations should be considered when interpreting the findings. First, country, institution, and academic-field composition are strongly confounded in the sample. Albania was primarily represented by STEM students, whereas the U.S. sample was primarily Business and Social Sciences. The comparisons therefore reflect a combined national, institutional, and disciplinary context rather than a clean country effect.

Second, the study relied on self-reported survey data. Responses about AI use, perceived learning value, and acceptable-use boundaries may be affected by recall, subjective interpretation, and social desirability, especially because academic AI use remains sensitive and unevenly governed.

Third, the study is cross-sectional. Student practices, institutional policies, and faculty expectations around generative AI are changing quickly, so the results capture one period of adoption rather than a stable long-term pattern.

Fourth, the attached analytic dataset did not include all labels and constructs described in the earlier manuscript draft. In particular, the exported workbook lacked a direct institutional-governance clarity item and the full multi-item AI self-efficacy scale, limiting the ability to test those constructs psychometrically.

Finally, the inferential analyses should be interpreted as exploratory. Chi-square tests, Mann-Whitney U tests, effect sizes, checklist alphas, and the high-frequency odds ratio improve the rigor of the descriptive results, but they do not establish causal relationships or fully adjust for the sample's institutional and disciplinary imbalance.

Conclusions

The findings of the present study demonstrate that generative AI has become a highly normalized component of undergraduate academic life across institutional and disciplinary contexts. Most students reported using AI tools regularly for school-related work, indicating that generative AI is no longer viewed

as an emerging or peripheral technology, but rather as an increasingly integrated element of contemporary learning practices.

At the same time, the study suggests that the educational implications of AI use cannot be understood through frequency of use alone. One of the central findings of the research is the distinction between learning-oriented AI use and substitution-oriented AI use. While many students reported using AI to support understanding, studying, brainstorming, and conceptual clarification, the findings also revealed evidence of substitution-oriented behaviors involving assignment generation, homework completion, and automation of academic work. Importantly, these patterns often coexisted, suggesting that undergraduate AI engagement exists on a continuum between reflective learning support and academic outsourcing.

The study also highlights the growing importance of AI literacy, AI self-efficacy, and prompt engineering competency in higher education. The findings suggest that the effective integration of AI into higher education depends not only on access to AI technologies but also on institutions' ability to foster critical evaluation skills, reflective engagement, responsible AI use, and self-regulated learning practices. Cross-cultural and institutional differences further demonstrated that educational context shapes how students integrate AI into academic work. Students from the U.S.-based institutions appeared more likely to use AI for workflow efficiency and productivity enhancement, whereas students from Albania relied more heavily on AI for conceptual explanation and tutorial-style support. These findings reinforce the importance of considering institutional culture, governance maturity, disciplinary context, and technological exposure when evaluating AI-supported learning practices.

Overall, the study contributes to the growing body of research examining generative AI in higher education by moving beyond simple measures of adoption and focusing instead on the educational orientation, literacy dimensions, and contextual factors shaping AI-supported academic behavior. By comparing undergraduate students from institutions in the United States and Albania, the study provides insight into how educational context influences AI-supported learning practices. The findings also demonstrate the value of distinguishing between learning-oriented and substitution-oriented AI use, showing that student engagement with generative AI exists on a continuum rather than within simple categories of acceptable and unacceptable behavior. Together, these findings contribute to a more nuanced understanding of how students integrate generative AI into their academic work and highlight the importance of AI literacy, prompting skills, and institutional guidance in shaping responsible use.

As generative AI technologies continue to evolve, higher education institutions will likely face growing pressure to balance innovation with governance by encouraging reflective, learning-oriented AI engagement while discouraging passive dependency and academically substitutive uses of AI technologies.

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Appendix A: Survey Instrument

Survey introduction: The survey focuses on how students are using and thinking about artificial intelligence. All answers are anonymous.

Note: All items were required in the original Microsoft Forms survey except the final open-response item. Response options are condensed here to reduce appendix length while preserving the full survey instrument.

About You			
Item	Question	Format	Response options
1	What year are you?	Single response	Freshman; Sophomore; Junior; Senior; Bachelor - Year 1 of 3; Bachelor - Year 2 of 3; Bachelor - Year 3 of 3; Other
2	Where do you go to school?	Single response	Polytechnic University of Tirana; Bentley University; Other
3	What is your major? If you have more than one, check them both.	Multi-select; maximum 2	Accounting; Business Analytics; Communication; Corporate Finance & Investments; Criminal Justice; Criminal Psychology; Digital & Social Media Marketing; Economics; Entrepreneurship; Finance; General Business; Hospitality, Events, & Tourism; Human Resource Management; International Business; Management; Marketing; Psychology; Real Estate Management; Sport Management; Sport Marketing & Content Creation; Sports Sales & Strategy; Engineering; Other

AI Awareness			
Item	Question	Format	Response options
4	Where did you first learn about using AI tools for schoolwork?	Single response	Friends or classmates; Social media; A teacher or professor; School workshop or training; I figured it out on my own; I haven't learned about this
5	Which of the following do you believe AI could help you with?	Select all that apply	Explaining difficult concepts; Summarizing readings; Creating practice questions or quizzes; Improving writing clarity; Generating complete assignment answers; I'm not sure what AI can help with
6	Do you know how to ask AI good questions to get helpful explanations?	Single response	Yes; Somewhat; No; I don't use AI
7	How confident are you in knowing how to use AI tools in a way that	Single response	Very confident; Somewhat confident; Not very confident; Not confident at all; I don't use AI

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Item	Question	Format	Response options
	supports learning, not just getting answers?		
8	Are you clear about school/class rules regarding AI use in assignments?	Single response	Very clear; Somewhat clear; Not very clear

AI Usage			
Item	Question	Format	Response options
9	Have you used AI tools for school-related work?	Single response	One or more times a day; One or more times a week; One or more times a month; Never
10	Have you ever asked AI to explain why it gave you the answer you received?	Single response	Often; Sometimes; Rarely; Never; I don't use AI
11	What do you mainly use AI for?	Select all that apply	Understanding a topic I don't get; Getting step-by-step explanations; Brainstorming ideas; Editing or improving my writing; Summarizing notes or readings; Creating study guides or flashcards; Getting answers to homework questions; Writing parts of assignments for me; I do not use AI
12	When using AI, how often do you try to understand the explanation rather than just copy the answer?	Single response	Always; Often; Sometimes; Rarely; Never; I don't use AI
13	Do you feel that using AI has improved your understanding of course material?	Single response	Yes; No; I don't use AI
14	Have you ever used AI to create practice questions or quizzes to test yourself?	Single response	Yes; No; I didn't know AI could do that
15	Which of the following do you think should be permitted uses of AI for classes?	Select all that apply	Writing an assignment from scratch; Helping study for a test; Generating ideas before I start writing; Solving homework problems; Checking grammar and clarity; Explaining a concept in simpler terms
16	Thank you for your participation. Any additional thoughts on AI you'd like to pass along?	Open response	Free-text response