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Self-Reported Generative AI Use Among Postsecondary Students: An Exploratory International Survey

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Abstract

This cross-sectional study examined reported GenAI use for academic work in 2022–23 and reported intention to use GenAI in 2023–24 among 1,021 English-fluent postsecondary students purposively recruited from multiple countries in September 2023. Descriptive statistics and exploratory, unadjusted Pearson chi-square tests examined bivariate associations with gender, primary-language category, and level-of-study category. Overall, 73.1% of participants reported using GenAI for academic work in 2022–23, and 65.6% reported intending to use it in 2023–24. Among GenAI users, 89.5% identified ChatGPT as the tool they used most. Statistically significant but small bivariate associations were found between gender and both outcomes, primary-language category and both outcomes, and graduate-versus-undergraduate category and reported use. No statistically significant association was detected between level-of-study category and reported intention. These findings provide a time-specific account of GenAI engagement within this multinational sample but do not establish population prevalence or independent demographic associations. They are compatible with selected aspects of postplagiarism, which served as an interpretive framework rather than a theory tested by the survey.

Keywords: generative artificial intelligence, GenAI, ChatGPT, student use, AI, PSE, quantitative

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Introduction

Within months of ChatGPT's public release, postsecondary institutions faced a basic empirical question: had students already begun using publicly available generative artificial intelligence (GenAI) for academic work, or had public debate moved ahead of student practice? Early scholarship identified possible educational applications, including brainstorming, writing support, personalized feedback, and research assistance. The same literature raised concerns about inaccurate or fabricated outputs, privacy, overreliance, inequitable access, academic integrity, and the continued validity of submitted work as evidence of student capability (Chan & Hu, 2023; Dawson et al., 2024; Ji et al., 2023; Miao & Holmes, 2023). These competing possibilities made student-reported use important to document without presuming that GenAI was either educationally beneficial or inevitably destined for unrestricted integration (Tagarro, 2025).

Empirical research emerging during this early period suggested considerable student awareness of and engagement with GenAI, although findings varied across institutional context, sampling strategy, and the meaning assigned to "use." Chan & Hu (2023), for example, found generally positive perceptions among undergraduate and postgraduate students while also documenting concerns about accuracy, privacy, ethical use, and overreliance. Johnston et al. (2024) found that more than half of respondents at one institution had used or considered using GenAI for academic purposes, but participants distinguished between limited assistance and using a tool to produce an entire assignment. Such studies provided valuable evidence while remaining specific to their samples and measures. They did not establish the prevalence of GenAI use among postsecondary students internationally.

This study contributes a time-specific account of reported GenAI engagement among English-fluent postsecondary students purposively recruited through Prolific from multiple countries in September 2023. It examines two related but distinct outcomes: retrospectively reported use of GenAI for academic work during the preceding year and prospectively reported intention to use GenAI during the following year. These outcomes capture reported use or nonuse and reported intention or non-intention. They do not measure frequency, intensity, purpose, educational quality, or observed behaviour.

Accelerating Technologies—A Review of GenAI Literature

GenAI integration in higher education has received significant attention, particularly regarding its adoption by university and college students globally. Research indicates that students generally hold positive perceptions of GenAI technologies, recognizing their potential to enhance learning experiences. Chan & Hu (2023) highlight that students appreciate the personalized learning support and assistance in writing and brainstorming that GenAI tools like ChatGPT provide, while Barrett & Pack (2023) note that when educators transparently model acceptable uses of GenAI, students adopt these tools more effectively in their writing processes. Recent findings by Kumar (2025) demonstrate positive attitudes toward GenAI among postsecondary education (PSE) students across disciplines, with students expressing enthusiasm about AI's potential to enhance learning efficiency and outcomes.

GenAI applications have expanded across specialized fields including medicine (Sauder et al., 2024), physics (Ding et al., 2023), computer science (Al-Jarf, 2024), and linguistics (Li et al.,

2024). Johnson et al. (2024) concluded that while AI will transform PSE institutions, the institutional system remains unprepared for this change, with faculty readiness lacking in many higher education contexts (Alnasib, 2023).

Research examining demographic differences in technology adoption has identified several key patterns. Prior research has identified gender-related differences in some dimensions of technology acceptance, integration, and confidence, although these patterns vary across contexts and technologies (Chen et al., 2019; Yau & Cheng, 2012). Educational level represents another significant factor, as individuals with higher education levels demonstrate greater inclination toward technology adoption (Dunne & Troske, 2005; Lane & Lyle, 2010). However, Henderson et al. (2017) found that advanced-degree students may be more discerning rather than resistant to AI adoption.

For students from diverse linguistic backgrounds, AI technologies can mitigate challenges associated with second-language learning environments. AI tools like ChatGPT and Duolingo have demonstrated effectiveness in improving language proficiency and fostering intercultural communication skills (Fountoulakis, 2024; Zhou & Hou, 2024), creating inclusive learning environments where students can practice without fear of making errors.

Prior research identified gender-related differences in some dimensions of technology acceptance, confidence, and adoption, although these patterns vary across technologies and contexts. Gender was therefore included as an exploratory demographic variable in this study. Because data collection occurred in September 2023, during an early stage of widespread public engagement with GenAI tools, we examined whether students' reported academic use of GenAI reflected patterns previously observed in the adoption of other technologies.

Alongside possible educational uses, scholarship identifies risks at the levels of learning, technical reliability, assessment, and the social conditions of AI production. Uncritical reliance may reduce opportunities for independent reasoning, evaluation, and fact-checking, particularly when instructional designs do not require students to scrutinize generated outputs. Large language models produce probabilistic text and may generate plausible but unsupported content (Ji et al., 2023). GenAI-assisted submissions also raise questions about whether assessments continue to provide valid evidence of student capability (Dawson et al., 2024). Wider concerns include privacy, unequal access, environmental costs, and the material and labour conditions involved in developing and maintaining AI systems (Bender et al., 2021; Crawford, 2021; Miao & Holmes, 2023). These concerns complicate accounts that treat GenAI integration as uniformly beneficial or inevitable (Tagarro, 2025).

As postsecondary institutions consider how to respond to GenAI, recent literature emphasizes necessary pedagogical shifts. Taylor (2023) argues that institutions considering AI-enhanced learning should provide support so that technological assistance complements rather than replaces critical thinking and creativity. Educators are exploring new assessment and instructional design forms that encourage critical engagement with AI tools. A U.S. national study by Johnson et al. (2024) underscores that while many institutions recognize the importance of integrating AI, infrastructural and resource constraints present significant adoption barriers in some regions.

Past research shows that AI offers new educational tools, but also raises concerns about cheating, trust, and fairness. However, limited evidence was available during the early period of public GenAI availability concerning whether students' reported academic use differed across demographic categories. The present study therefore examines reported GenAI use and reported intention to use GenAI in relation to gender, primary-language, and level-of-study categories, while treating these as exploratory comparisons rather than causal explanations.

Why Examine Demographic Variation?

Data collection occurred during an early stage of widespread public engagement with GenAI, when empirical evidence concerning which student characteristics, if any, might correspond with reported academic use remained limited. Gender, primary-language category, and level-of-study category were therefore selected in advance as exploratory variables rather than as presumed causes of GenAI use. Prior technology adoption research had identified gender-related variation in some contexts, although findings varied across technologies and settings (Chen et al., 2019; Venkatesh et al., 2003; Yau & Cheng, 2012). Research concerning additional-language learning suggested that AI-supported tools might offer writing, feedback, and communication assistance that could be particularly relevant to some multilingual learners (Fountoulakis, 2024; Zhou & Hou, 2024). Level of study also offered a plausible exploratory comparison because graduate and undergraduate students may encounter different disciplinary expectations, research tasks, and institutional contexts.

There are also reasons to interpret demographic comparisons cautiously. Categories such as gender, primary language, and level of study do not provide self-sufficient explanations for technology use. Differences between categories may overlap with discipline, programme type, institutional policy, assignment requirements, access to paid tools, age, prior technological experience, and other measured or unmeasured conditions. Demographic comparisons may also conceal substantial variation within categories. The analyses in this study were consequently designed to identify unadjusted bivariate patterns within the sample, not to establish independent demographic relationships or to attribute reported GenAI use to demographic identity.

Postplagiarism as an Interpretive Framework

Postplagiarism describes an emerging ethical and educational context in which advanced technologies become increasingly incorporated into human writing, learning, and knowledge production (Eaton, 2023). Its six tenets concern the normalization of hybrid human–AI writing; the relationship between human creativity and technological assistance; the facilitation of communication across languages; continuing human responsibility for technologically assisted work; the importance of attribution; and the need to reconsider historically bounded understandings of plagiarism. The framework moves discussion beyond the binary question of whether technological assistance constitutes misconduct and directs attention toward authorship, responsibility, attribution, creativity, and human–technology collaboration.

In this study, postplagiarism serves as an interpretive framework rather than a testable explanatory theory. The survey was not developed from the six tenets and did not operationalize creativity, attribution, responsibility, acceptability, human–AI co-authorship, or changes in

linguistic barriers. Gender and level of study are not variables specified by the framework, and the primary-language item did not measure whether GenAI reduced communication barriers. Findings may therefore be considered compatible with selected aspects of postplagiarism, particularly its account of increasingly common human–GenAI interaction, but they cannot confirm the framework or establish that it explains reported use.

Postplagiarism also differs in purpose from technology-adoption models such as the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT explains technology-use intentions and behaviour through constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, with demographic and experiential characteristics functioning as moderators (Venkatesh et al., 2003). The present survey did not measure these constructs and therefore cannot compare the explanatory performance of postplagiarism and UTAUT. Prior technology-adoption scholarship informed the exploratory decision to examine demographic variation; postplagiarism was applied subsequently as one interpretive lens through which to consider the findings.

The absence of gender as a central variable within postplagiarism should not be treated as a prediction that gender differences will not occur. However, comparatively high reported-use proportions among both female and male participants may be described as compatible with the framework's broader account of increasingly common human–GenAI interaction. Such an interpretation does not negate statistically significant associations, establish equivalence between groups, demonstrate that demographic differences are disappearing, or make structural inequalities irrelevant.

Study Purpose

The study examined reported GenAI engagement among a purposively recruited international sample of postsecondary students at a particular point in the development and public availability of GenAI. It addressed the following questions:

1. What proportions of participants reported using GenAI for academic work during the preceding year and intending to use GenAI during the following year?
2. Which GenAI tool did participants who reported use identify as the tool they used most?
3. Were reported GenAI use and reported intention to use GenAI bivariately associated with gender, primary-language category, or level-of-study category?

The study provides descriptive and exploratory evidence from this multinational sample. It does not estimate prevalence among postsecondary students worldwide, directly observe GenAI use, nor identify independent demographic determinants.

Understanding PSE Students' Use Patterns

This pilot research project employed a cross-sectional survey design, meaning data were collected from many English-fluent PSE students recruited through Prolific across multiple countries at a single point in time (Ho et al., 2006). The first part of the survey collected volunteer participants' demographic information, including whether they were graduate or undergraduate students, the gender they identified with, whether their primary language was English, and the country in which they resided. After recording this demographic information, the

participants were asked if they used GenAI tools (such as ChatGPT, DALL-E, and Midjourney) to do their academic work. The survey also asked which tool they used the most. Participants were also asked if they intended to use GenAI tools to do their academic work in the 2023−24 academic year. A text box was also provided where they could articulate reasons for their choices. This descriptor was intended to understand the reasons PSE students give for using GenAI tools. In the survey's last segment, participants were also asked what would change their decision: If they used GenAI tools in the past, what would sway their decision to stop using them; conversely, if they did not use GenAI tools, what would cause them to start using such tools? The rationale for this question was to identify external or internal factors that shaped PSE students' decision to use or forego GenAI tools.

Survey Instrument

The authors developed a brief questionnaire for this exploratory study. The questionnaire included demographic items and single-item questions asking whether participants had used artificial intelligence programs for academic or schoolwork during the preceding year and whether they intended to use such programs during the following year. The reported-use item provided ChatGPT, DALL-E, and MidJourney as examples but did not supply a formal definition of GenAI or academic work. Because data collection occurred in September 2023, the preceding-year and following-year items were interpreted as referring broadly to the 2022–23 and 2023–24 academic years, respectively. Participants were also asked which AI software they had used most and were invited to provide open-text explanations. The primary outcomes were single-item categorical measures; therefore, internal consistency reliability was not applicable. No formal psychometric validation was conducted. The complete instrument appears in the Appendix.

The survey tool was created in Qualtrics and underwent a research ethics review and clearance. Participation was solicited using the Prolific online research platform. This is part of a purposive sampling approach through Prolific's participant pool. Participation was limited to those fluent in English. Participants were compensated for their time using Prolific's financial incentive rates. Ballot stuffing and bot use were prevented. The participation pool was limited to registered Prolific users attending college or university. The data were collected in September 2023.

The data underwent a purification process before being transferred to IBM SPSS for further analysis. The optional open-text responses were reviewed only to identify illustrative examples. They were not systematically coded, quantified, or compared across demographic categories and were not used to estimate the prevalence of particular views. Three principal analytical procedures were executed on the quantitative data: Firstly, general descriptive statistics were generated to provide an initial overview of the dataset's characteristics. Second, we conducted exploratory bivariate analyses using Pearson chi-square tests of independence to examine the unadjusted association between each demographic characteristic - gender, primary language, and level of study - and two binary outcomes: retrospectively reported GenAI use for academic work during the 2022–23 academic year and prospectively reported intention to use GenAI for academic work during the 2023–24 academic year. Phi coefficients were calculated to assess the strength of each bivariate association. Lastly, standardized residuals were examined to

identify cells in the contingency tables that contributed to statistically significant overall associations. These analyses did not estimate the independent association of each demographic characteristic or account for overlap or potential confounding among the demographic variables. Because several related bivariate tests were conducted without adjustment for multiple comparisons, the results are treated as exploratory and interpreted cautiously.

Illustrative open-text responses referred to using GenAI for the “wording of sentences” (participant #619), as a “search tool” (participant #898), as an “encyclopedia” (participant #481), and to generate practice questions (participants #283 and #562). These examples are included only to illustrate the range of uses mentioned by individual participants. The responses were not systematically coded or used to estimate the prevalence of particular uses.

Findings and Discussion

In all, 1,021 individuals participated in the study; 50.5% identified as female (n=516) and 48.7% as male (n=497). Most participants (80.2%) were undergraduate students (n=819), and only 19% were graduate students (n=194). The mean and median times for participants to complete the survey were 5.5 and 4.2 minutes, respectively. Among participants reporting GenAI use, ChatGPT was the tool identified most often (*n* = 668), representing 65.4% of the full sample and 89.5% of participants who reported using any form of GenAI. Overall, 73.1% of participants (*n* = 746) reported using GenAI for academic work in 2022–23, and 65.6% (*n* = 670) reported intending to use it in 2023–24.

Gender Differences in Usage and Planned Future Use

Table 1 presents reported GenAI use by gender.

Table 1
Use of GenAI in 2022−23 by Gender

Gender	Used AI	Did not use AI	Undisclosed	Total
Male	398	93	6	497
Female	344	170	2	516
Transgender	3	2	0	5
Non-binary	0	1	0	1
Other	1	0	0	1
Undisclosed	0	1	0	1
Total	746	267	8	1,021

Note.

This table provides descriptive data; the low-value entries were omitted for Chi-Squares calculated subsequently.

The data revealed that proportionately more males (81.1%) than females (66.9%) used AI, consistent with Nouraldeen's (2022) findings indicating males were more inclined to adopt AI than females. A Pearson chi-square test of independence identified a statistically significant bivariate association between gender and self-reported GenAI use, $\chi^2(1, N = 1,005) = 25.96$, $p < .001$. The Phi coefficient of .161 indicated that the association was small in magnitude.

For the inferential cross-tabulation analysis, male and female categories were isolated due to insufficient sample sizes in other gender categories, with a binary variable (IsMale) created for statistical comparison. Participants who did not provide a valid yes/no response to the GenAI-use question were also excluded. The cross-tabulation analysis with standardized residuals revealed significant patterns, as illustrated in Table 2.

The standardized residual analysis revealed that significantly more females than expected reported not using AI (residual = 3.10), while significantly fewer males than expected reported not using AI (residual = −3.10). However, the low Phi-coefficient indicates that while statistically significant, the practical association between gender and AI usage remains minimal.

We next examined participants' prospectively reported intentions to use GenAI for academic work in 2023–24. Table 3 presents the descriptive distribution of responses by gender.

After excluding missing and "prefer not to disclose" responses, a higher proportion of male respondents (74.5%) than female respondents (63.3%) reported that they intended to use GenAI for academic work in 2023–24. A Pearson chi-square test of independence identified a

Table 2

Cross-tabulation with Residuals and Expected Counts for GenAI Used in 2022−23 by Gender

Gender	Measure	Did not use GenAI (0)	Used AI (1)	Total
Female (IsMale = 0)	Observed count	170	344	514
	Expected count	134.5	379.5	514
	Standardized residual	3.1	−1.8	
Male (IsMale = 1)	Observed count	93	398	491
	Expected count	128.5	362.5	491
	Standardized residual	−3.1	1.9	
Total	Observed count	263	742	1,005
	Expected count	263	742	1,005

Note.

The analysis included participants who identified as female or male and provided a valid yes/no response to the GenAI-use question. Other gender categories were reported descriptively in Table 1 but excluded from the inferential analysis because of low counts. Eight participants who identified as female or male and selected "prefer not to disclose" for GenAI use were also excluded.

Table 3
Self-Reported Intention to Use GenAI in 2023–24 by Gender

Gender	Intend to use	Do not intend to use	Prefer not to disclose	Total
Male	353	121	23	497
Female	314	182	18	514
Transgender	2	3	0	5
Non-binary	0	1	0	1
Other	1	0	0	1
Undisclosed	0	1	0	1
Total	670	308	41	1,019

Note.

This table presents descriptive responses for all gender categories. Two participants did not provide a response to the intention item; therefore, the total is 1,019 rather than 1,021. The subsequent inferential analysis was restricted to participants who identified as female or male and provided a valid yes/no response. Other gender categories were excluded from the inferential analysis because of sparse cell counts.

statistically significant bivariate association between gender and reported intention to use GenAI, $\chi^2(1, N = 970) = 14.07$, $p < .001$. The Phi coefficient of .120 indicated a small association, reflecting a directional pattern similar to that observed for reported GenAI use in 2022–23.

Table 4 presents the observed counts, expected counts, and standardized residuals for the 970 valid cases included in the analysis.

The largest deviations from the expected counts occurred among respondents who reported that they did not intend to use GenAI. More female respondents than expected selected this response (standardized residual = 2.20), while fewer male respondents than expected selected it (standardized residual = −2.20). The standardized residuals for intending to use GenAI were smaller in magnitude: −1.50 for female respondents and 1.50 for male respondents. Although the chi-square test was statistically significant, the Phi coefficient indicated a small bivariate association between gender and reported intention to use GenAI.

Across the two segments of having used GenAI in 2022-23 and intending to use GenAI in 2023-24, there are similar gender-related patterns: male respondents reported higher rates of previous GenAI use and intended future use of GenAI than female respondents. This direction is consistent with Nouraldeen's (2022) findings and with some prior research (Venkatesh et al., 2003) reporting gender-related differences in technology adoption. But the Phi coefficients of .161 for reported use and .120 for reported intentions suggest that the bivariate associations

Table 4
Cross-Tabulation of Reported Intention to Use GenAI in 2023–24 by Gender

Gender	Measure	Do not intend to use AI (0)	Intend to use AI (1)	Total
Female	Count	182	314	496
	Expected count	154.9	341.1	496
	Standardized residual	2.2	−1.5	
Male	Count	121	353	474
	Expected count	148.1	325.9	474.0
	Standardized residual	−2.2	1.5	
Total	Count	303	667	970
	Expected count	303	667	970

Note.

The analysis included participants who identified as female or male and provided a valid yes/no response to the question about their intention to use GenAI in 2023–24. Other gender categories were reported descriptively in Table 3 but excluded from the inferential analysis because of sparse cell counts. Forty-one participants who identified as female or male selected “prefer not to disclose,” and two female participants did not provide a response; these cases were excluded from the analysis.

were small. Because the demographic variables were examined separately, these analyses do not claim that gender is an independent determinant of GenAI past or future use. The observed differences may also reflect other factors that were either not collected or not measured – such as instructor policies on GenAI use in the syllabus, institutional policies regarding the use or restriction of GenAI, proficiency with GenAI tools, and even access to tools, as access is uneven.

Postplagiarism (Eaton, 2023) does not identify gender as a central determinant of human–GenAI interaction. The comparatively high reported-use proportions observed among both female and male participants may therefore be considered compatible with the framework’s broader account of increasingly common human–GenAI interaction. This interpretation does not negate the statistically significant gender associations found in the sample, establish demographic equivalence, or confirm postplagiarism as an explanatory theory.

English as a Subsequent Language Versus English Speakers’ Use of GenAI

The survey asked participants if English was their primary language. Only 56% of the respondents (n=572) reported having English as their primary language, although every

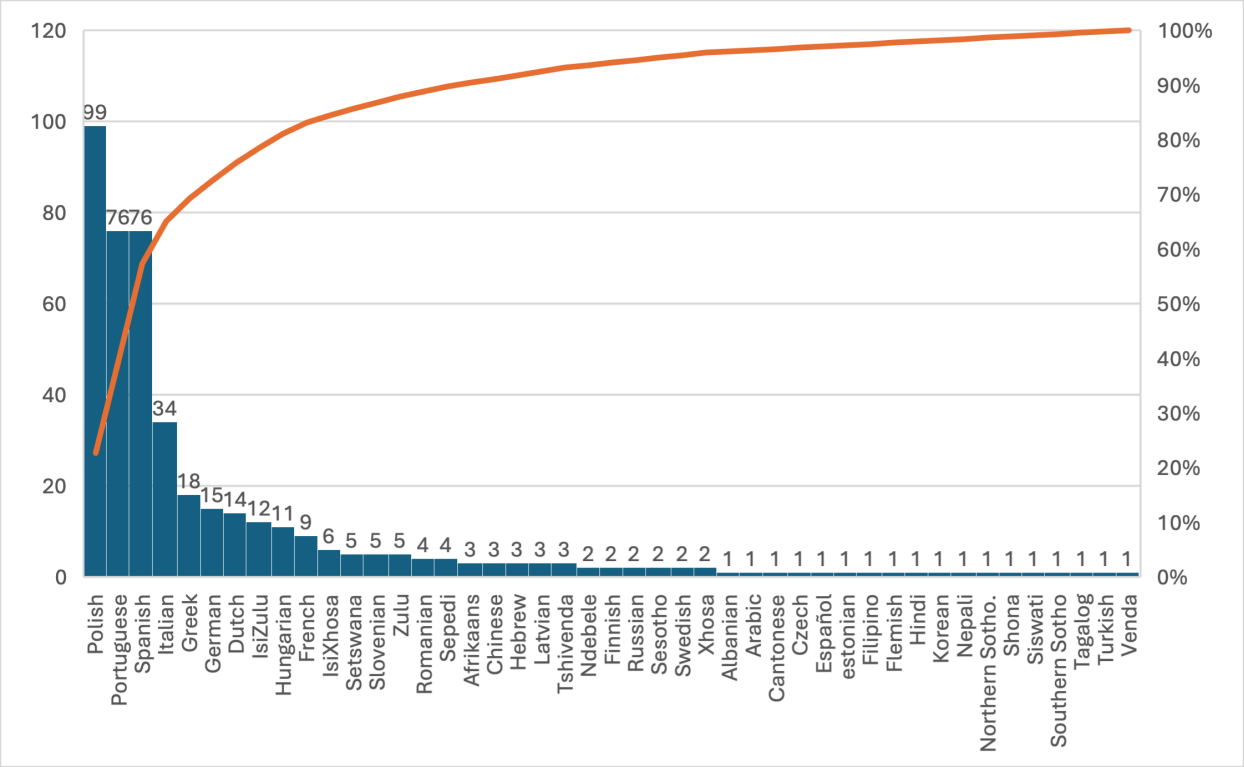
respondent was fluent in English (which was a criterion for participating in the research). Participants whose primary language was not English represented 42.9% of the sample(n=438), with the top primary languages being Polish, Portuguese, and Spanish, based on Prolific platform recruitment, as shown in Figure 1.

Among participants with valid primary-language and reported-use responses, 70.4% of those whose primary language was English reported GenAI use, compared with 78.1% of those whose primary language was not English (Figure 2). The corresponding proportions reporting nonuse were 29.6% and 21.9%, respectively.

A Pearson chi-square test indicated a statistically significant association between primary-language category and reported GenAI use in 2022–23, $\chi^2(1, N = 1,004) = 7.655$, $p = .006$. The association was small, $\phi = -.087$. None of the standardized residuals reached the prespecified absolute threshold of 2.00, so no individual cell can be identified as statistically notable.

Cross-tabulation analysis was conducted using a new binary variable (IsEng), where 1 indicated English as the primary language, and 0 indicated a non-English language. Responses for "prefer not to disclose" or lacking a valid primary-language response were treated as missing. The analysis included 1,004 responses. Table 5 shows the observed counts, expected counts, row percentages, and standardized residuals.

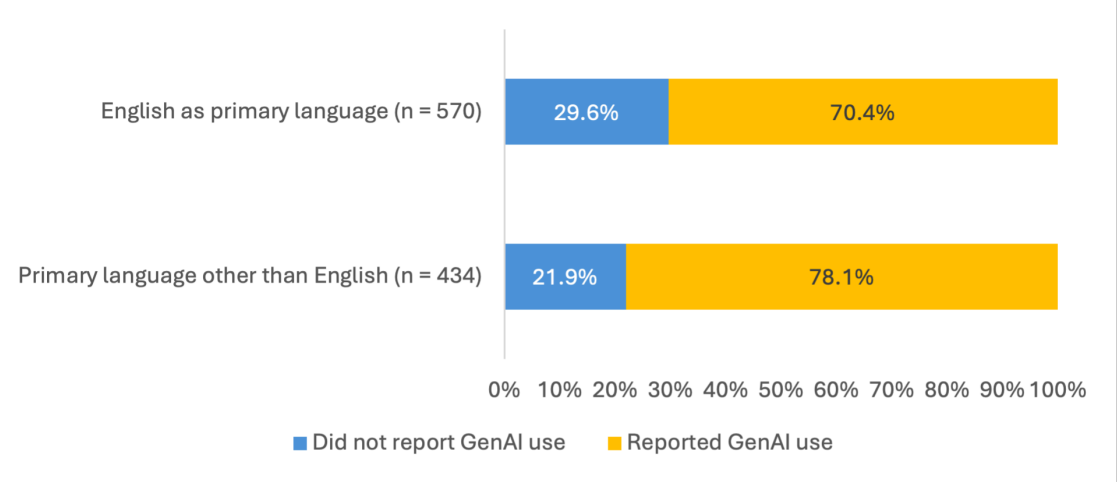
Figure 1: *Distribution of Participants' Primary Language (Other than English)*



Note.

The orange line represents the accounting of the participant population.

Figure 2: Reported GenAI Use in 2022-23 by Primary Language Category



Note.

Percentages are calculated within primary-language category among participants with valid primary-language and yes/no reported-use responses ($N = 1,004$). 17 participants were excluded because they did not provide responses to one or both variables.

Participants whose primary language was not English reported nonuse less often than expected under the assumption of independence (standardized residual = −1.79), whereas participants whose primary language was English reported nonuse somewhat more often than expected (standardized residual = 1.56). However, none of the standardized residuals reached the prespecified absolute threshold of 2.00. Accordingly, no individual cell was identified as statistically notable.

A Pearson chi-square test indicated a statistically significant association between primary-language category and reported intention to use GenAI in 2023–24, $\chi^2(1, N = 970) = 8.337$, $p = .004$. The association was small, $\phi = -.093$. The analysis included respondents with valid primary-language and valid yes/no intention responses. Table 6 presents the observed counts, expected counts, row percentages, and standardized residuals.

The two primary-language analyses produced similar results. Primary-language category was statistically associated with both reported GenAI use in 2022-23, χ2 (1, *N* = 1,004) = 7.655, $p = .006$, $\phi = -.087$, and reported intention to use GenAI in 2023-24, χ2(1, *N* = 970) = 8.337, $p = .004$, $\phi = -.093$. In both cases, the bivariate association was small, and no standardized residual reached the pre-established threshold of |2.00|. Participants whose primary language was not English reported GenAI use and intention somewhat more frequently than participants whose primary language was English. But the analyses do not establish that primary language accounted for these differences.

Prior research suggests that AI tools may support some aspects of additional-language learning, writing, feedback, and engagement. For example, Zhou & Hou (2024) examine how AI may influence the engagement of English-as-a-foreign-language teachers and learners. Such

research provides a possible context for the pattern observed here, but it does not directly explain differences in GenAI adoption between primary-language groups.

Several alternative explanations remain plausible. Primary language may overlap with other demographic variables, or differences in how respondents interpreted “academic work.” The

Table 5

Cross-tabulation with Residuals and Expected Counts for GenAI Used in 2022–23 by English Language

Language	Measure	Did not use GenAI	Used GenAI	Total
Primary language other than English	Observed count	95	339	434
	Row percentage	21.9%	78.1%	100.0%
	Expected count	114.1	319.9	434.0
	Standardized residual	−1.79	1.07	
English as primary language	Observed count	169	401	570
	Row percentage	29.6%	70.4%	100.0%
	Expected count	149.9	420.1	570
	Standardized residual	1.56	−0.93	
Total	Observed count	264	740	1,004
	Row percentage	26.3%	73.7%	100.0%
	Expected count	264	740	1,004

Note.

Percentages are calculated within primary-language category. The analysis included respondents with valid primary-language and valid yes/no reported-use responses. Seventeen participants were excluded because they lacked a valid response to one or both variables. Standardized residuals were interpreted using an absolute threshold of 2.00.

Table 6

Cross-tabulation with Residuals and Expected Counts for Intending to Use AI in 2023–24 by English Language

Language	Measure	Intend not to use AI	Intend to use AI	Total
Primary language other than English	Observed count	113	315	428
	Row percentage	26.4%	73.6%	100.0%
	Expected count	133.7	294.3	428
	Standardized residual	−1.79	1.21	
English as primary language	Observed count	190	352	542
	Row percentage	35.1%	64.9%	100%
	Expected count	169.3	372.7	542
	Standardized residual	1.59	−1.07	
Total	Observed count	303	667	970
	Row percentage	31.2%	68.8%	100%
	Expected count	303	667	970

Note.

Percentages are calculated within primary-language category. The analysis included respondents with valid primary-language and valid yes/no intention responses. Fifty-one participants were excluded because they lacked a valid response to one or both variables: 11 lacked a valid primary-language response, 43 lacked a valid intention response, and three lacked valid responses to both items. Standardized residuals were interpreted using a threshold of |2.00|.

requirement that all participants be fluent in English in order to participate in this research may also have reduced differences between the language groups. In addition, the survey did not measure English proficiency, native-speaker status, the purposes for which participants used GenAI, the frequency or intensity of use, or whether GenAI improved their academic writing.

The findings may be interpreted as compatible with the aspect of postplagiarism concerned with the potential for technology to reduce some linguistic barriers (Eaton, 2023; Kumar, 2025). They do not demonstrate that language barriers diminished or disappeared. Postplagiarism served as

an interpretive framework rather than a theory directly tested by these variables, and the survey did not operationalize language-barrier reduction. Eaton's (2023) formulation itself clarifies that the tenet was not intended to suggest that a person's first language becomes unimportant, only that communication is easily facilitated using GenAI. Therefore, the results should be understood as exploratory within this international sample. They cannot establish an independent relationship between primary language and GenAI use, explain why the associations occurred, or support population-level conclusions about postsecondary students worldwide. Future research could collect additional demographic and contextual variables and examine how they jointly explain reported GenAI use.

Level-of-Study Category, Reported GenAI Use, and Intention

Among the 1,013 participants who provided a valid level-of-study response, 194 (19.2%) were graduate students and 819 (80.8%) were undergraduate students. Separate exploratory bivariate analyses examined level-of-study category in relation to retrospectively reported GenAI use in 2022–23 and prospectively reported intention to use GenAI in 2023–24.

For the 2022–23 analysis, complete cases were required for both level-of-study category and reported GenAI use. The analysis included 1,005 participants, comprising 193 graduate students and 812 undergraduate students. Sixteen participants were excluded: eight lacked a valid level-of-study response, and a different eight lacked a valid reported-use response. Table 7 presents the observed counts, row percentages, expected counts, and standardized residuals.

Graduate students reported GenAI use more frequently than undergraduate students, at 80.3% and 72.2%, respectively. The overall Pearson chi-square test revealed a statistically significant association between level-of-study category and reported GenAI use, $\chi^2(1, N = 1{,}005) = 5.339$, $p = .021$. The Phi coefficient indicated a small bivariate association, $\phi = -.073$. No standardized residual reached the prespecified threshold of |2.00|. Thus, although the test indicated an association across the table, no individual cell deviation met the criterion for being identified as statistically notable.

The second analysis examined level-of-study category in relation to reported intention to use GenAI in 2023–24. Participants again required valid responses for both variables. The complete-case analysis included 971 participants, comprising 186 graduate students and 785 undergraduate students. Table 8 presents the observed counts, row percentages, expected counts, and standardized residuals.

Graduate students reported an intention to use GenAI somewhat more frequently than undergraduate students, at 72.6% and 67.6%, respectively. The Pearson chi-square test did not detect a statistically significant bivariate association between level-of-study category and reported intention to use GenAI, $\chi^2(1, N = 971) = 1.701$, $p = .192$. The Phi coefficient was small, $\phi = -.042$, and no standardized residual reached the prespecified threshold of |2.00|. This result does not establish that no association exists in the wider population; rather, the analysis did not detect one in this purposively recruited sample.

The two analyses produced different results. Level-of-study category had a statistically significant but small bivariate association with retrospectively reported GenAI use in 2022–23,

Table 7
Reported GenAI Use in 2022–23 by Level-of-Study Category

Level of Study	Measure	Did not use AI	Used AI	Total
Graduate	Observed count	38	155	193
	Row percentage	19.7%	80.3%	100%
	Expected count	50.7	142.3	193
	Standardized residual	−1.78	1.06	
Undergraduate	Observed count	226	586	812
	Row percentage	27.8%	72.2%	100%
	Expected count	213.3	598.7	812
	Standardized residual	0.87	−0.52	
Total	Observed count	264	741	1,005
	Row percentage	26.3%	73.7%	100%
	Expected count	264	741	1,005

Note.

The analysis includes participants with valid responses for both level-of-study category and reported GenAI use in 2022–23. Eight participants with missing level-of-study data and eight different participants with missing reported-use data were excluded. Pearson $\chi^2(1, N = 1{,}005) = 5.339$, $p = .021$, $\phi = -.073$. No expected count was below 5; the minimum expected count was 50.70. Standardized residuals were evaluated using an absolute threshold of $|2.00|$.

whereas we did not detect a statistically significant bivariate association with prospectively reported intention to use GenAI in 2023–24. This difference may partly reflect the distinction between reporting previous behaviour and stating a future intention. Johnston et al. (2024) similarly found that students' use or contemplated use of GenAI technologies did not appear to differ by level of study, although their combined measure differed from the two binary outcomes used here. Other research has found differences among student classifications in GenAI comprehension, proficiency, perceived benefits, and concerns, indicating that results may depend on the outcome being measured (Maxwell et al., 2025).

Some participants in this study noted field-specific limitations, including AI-generated "hallucination" of nonexistent references (participant #251) and reduced usefulness in "niche scientific fields" (participant #872). These comments may help contextualize why some graduate students reported limited engagement with GenAI, but they cannot explain the aggregate association because the responses were not systematically compared by level-of-study category. Differences in discipline, programme type, research demands, assignment requirements, institutional policy, access, age, and prior technological experience may also

Table 8
Reported Intention to Use GenAI in 2023–24 by Level-of-Study Category

Level of Study	Measure	Do not intend to use AI	Intend to use AI	Total
Graduate	Observed count	51	135	186
	Row percentage	27.4%	72.6%	100%
	Expected count	58.4	127.6	186
	Standardized residual	−0.97	0.66	
Undergraduate	Observed count	254	531	785
	Row percentage	32.4%	67.6%	100%
	Expected count	246.6	538.4	785
	Standardized residual	0.47	−0.32	
Total	Observed count	305	666	971
	Row percentage	31.4%	68.6%	100%
	Expected count	305	666	971

Note.

The analysis includes participants with valid responses for both level-of-study category and reported intention to use GenAI in 2023–24. Pearson $\chi^2(1, N = 971) = 1.701$, $p = .192$, $\phi = -.042$. Standardized residuals were evaluated using an absolute threshold of |2.00|.

overlap with level of study. The unadjusted analyses therefore cannot establish an independent association between level-of-study category and either outcome.

The binary measures also do not capture frequency, purpose, intensity, or context of GenAI use. Nevertheless, the relatively high reported-use and intention proportions in both groups may be viewed as compatible with postplagiarism's account of increasingly common human–GenAI interaction. They do not confirm postplagiarism as an explanatory theory or establish that level-of-study differences are disappearing.

Limitations and Contextualization

This study should be interpreted in light of several limitations. First, participants were purposively recruited from Prolific rather than through open international sampling, and eligibility required both registration on the platform and English fluency. Although participants resided in several countries, the findings describe this purposively recruited multinational sample and should not be generalized to postsecondary students worldwide (Bethlehem, 2010).

Second, the outcomes were measured through single-item binary self-reports. Reported GenAI use in 2022–23 required retrospective recall, whereas reported intention to use GenAI in 2023–24 concerned a future intention and does not establish subsequent behaviour (Sheeran & Webb, 2016). Self-reports may also have been affected by social-desirability pressures, reluctance to disclose potentially prohibited use, differences in how participants interpreted "GenAI" and "academic work," or inaccurate recall. Because the outcomes were single items, internal-consistency reliability was not applicable, and the study did not validate responses against observed use or platform records. The binary measures did not capture frequency, intensity, purpose, quality, context, or observed behaviour. The optional open-text responses were used illustratively and not compared across demographic categories.

Third, the demographic analyses were exploratory and unadjusted. The separate chi-square tests did not estimate independent demographic associations or account for overlap and potential distortion across gender, primary language, and level-of-study categories. Several related tests were conducted without adjustment for multiple comparisons, increasing the need for cautious interpretation. The analyses also did not jointly examine discipline, program type, institution, country, assignment requirements, policy, access, age, or prior technological experience. Valid-case totals differed because some participants did not answer certain items or selected the nondisclosure options. These exclusions reduced the information available for individual analyses.

Finally, data collected in September 2023 provide a time-specific snapshot from an early period of widespread public engagement with GenAI. Subsequent changes in tools, access, costs, policies, and instructional practices may limit the findings' current applicability. Reported prevalence therefore should not be interpreted as evidence that GenAI use was educationally beneficial, institutionally acceptable, normalized, or inevitable (Dawson et al., 2024; Ji et al., 2023). Future studies should address these limitations for more generalizability.

Conclusion

This exploratory study provides a time-specific account of GenAI engagement among a purposively recruited multinational sample of postsecondary students. In September 2023, 73.1% of participants reported using GenAI for academic work during the 2022-23 academic year, and 65.6% reported intending to use GenAI for academic work during 2023-24. Among participants who reported GenAI use, 89.5% identified ChatGPT as the tool they used most. These figures document substantial early engagement with GenAI during a formative period in its public uptake, while representing this sample rather than population-level prevalence among postsecondary students internationally.

The exploratory, unadjusted demographic analyses identified small bivariate associations between gender and both reported GenAI use and reported intention to use GenAI, and between primary-language category and both outcomes. Level-of-study category, comparing graduate and undergraduate students, had a small bivariate association with reported GenAI use, but the analysis did not detect a statistically significant association with reported intention. These analyses do not establish independent demographic associations, and the non-significant result should not be interpreted as evidence that undergraduate and graduate students were equivalent. The relatively high proportions reported across the examined categories may be

viewed as compatible with postplagiarism's account of increasingly common human–GenAI interaction (Eaton, 2023), but they do not confirm the framework, demonstrate that demographic differences are disappearing, or establish that GenAI use transcends demographic or structural inequalities.

Additionally, the reported use of GenAI within this sample indicates a need for clear policies, transparent expectations, and teaching practices that distinguish acceptable assistance from uses that undermine learning or misrepresent student achievement. This approach also retains postplagiarism's emphasis on human responsibility for work produced with technological assistance, without presuming that GenAI use is inevitable or uniformly educationally beneficial. Institutions should consider possible educational applications alongside concerns about inaccurate or probabilistic outputs, overreliance, inequitable access, academic credibility, and assessment validity. Demographic and structural differences should remain part of this work because small bivariate associations do not make inequalities in access, experience, or consequences irrelevant.

Future research should examine how students use GenAI, the purposes and contexts of that use, and the reasons underlying decisions to use or avoid particular tools. Qualitative and mixed-methods studies could investigate how students interpret institutional expectations and negotiate questions of authorship, learning, credibility, and responsibility. Longitudinal and multivariable research could also assess how reported use and behaviour change alongside developments in technology, access, assessment practices, and institutional policy. Such work would provide a stronger basis for evaluating whether and under what conditions human–GenAI interaction becomes an established feature of postsecondary education.

Author's Contributions

R.K. and R.M. contributed equally to all stages of this work, including the conception, design, literature review, analysis, and manuscript drafting and revision. Both authors read and approved the final manuscript.

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Ethics Statement

This study was approved by the Research Ethics Board (File # 22-264 – KUMAR) and the protocol was adhered to throughout the research.

Conflict of Interest

The researchers and authors have no conflict of interest to declare.

Data Availability Statement

Ethics clearance prohibits data sharing because the consent form the participants signed did not include terms for data sharing.

Abbreviations

AI
Artificial Intelligence

GenAI
Generative Artificial Intelligence

GPT
Generative Pre-trained Transformer

LLM
Large Language Model

PSE
Postsecondary Education

UTAUT
Unified Theory of Acceptance and Use of Technology

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Appendix

Survey Instrument

Note. The following reproduces the substantive survey items administered through Qualtrics in September 2023. Participant-information and consent materials, investigator contact information, the Prolific identification field, and the completion-code page have been omitted because they served administrative rather than analytic purposes. The wording and response options have otherwise been retained.

Demographic information

1. Please indicate your department affiliation.
    - [Dropdown response]
2. Please indicate your level of current study.
    - Undergraduate
    - Graduate
    - Other
3. What year of the program are you currently in? Please enter the nearest whole number. (If you prefer not to disclose, enter 0.)
    - [Numeric response]
4. Gender with which you identify?
    - Male
    - Female
    - Transgender
    - Two spirited
    - Non-binary
    - Other
    - Prefer not to disclose
5. Is English your first language or primary language?
    - Yes
    - No, my primary language is: [Text response]
    - Prefer not to disclose

AI questions

6. Have you used artificial intelligence (like ChatGPT or DALL-E or MidJourney) programs since the last year to do your academic or schoolwork?
    - Yes
    - No
    - Prefer not to disclose

7. Which AI software did you use the most?
    - [Open-text response]
8. Do you intend to use artificial intelligence programs to do your academic or schoolwork next year?
    - Yes
    - No
    - Prefer not to disclose
9. Which AI tool do you intend to use?
    - [Open-text response]
10. Why (or why not) do you use (or intend to use) artificial intelligence programs?
    - [Open-text response]
11. Based on your answer above, what would change your decision?
    - [Open-text response]
12. Is there anything else you would like to tell us about this topic of AI use to do academic work?
    - [Open-text response]