

Article

Generative AI in Higher Education: A Large-Scale Study of Student Usage Patterns, Applications and Motivations

Avraam Chatzopoulos , Paraskevi Zacharia *  and Antreas Kantaros 

Department of Industrial Design and Production Engineering, University of West Attica, Egaleo, 12241 Athens, Greece; xatzopoulos@uniwa.gr (A.C.); akantaros@uniwa.gr (A.K.)

* Correspondence: p.zacharia@uniwa.gr; Tel.: +30-210-538-1055

Abstract

The rapid adoption of Generative Artificial Intelligence (GenAI) tools is transforming learning practices in higher education, raising important questions about their educational value and impact on student learning. This study examines how university students use GenAI tools in both academic and everyday contexts, with emphasis on usage patterns, applications and motivations. A large-scale voluntary survey was conducted with 788 undergraduate students from a single public university in Greece, with respondents drawn from multiple schools and disciplines. Data were collected through an online questionnaire and analyzed using descriptive and inferential statistical methods to explore frequency of use, application categories and motivations for engagement with GenAI tools. The results indicate a high level of reported GenAI engagement among the participants, with ChatGPT emerging as the most frequently used tool. Students primarily rely on GenAI tools for information searching, understanding academic content and supporting academic tasks, while creative and entertainment-related uses are less frequent. Overall, the findings suggest that students perceive GenAI tools as useful for learning support and efficiency improvement. The results indicate that GenAI tools are becoming integrated into students' reported learning practices. They also highlight the need for clear pedagogical guidelines and systematic AI literacy integration in teaching and learning.

Keywords: generative artificial intelligence; higher education; university students; artificial intelligence in education; large language models; ChatGPT; student usage patterns; AI tools



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1. Introduction

The integration of Artificial Intelligence (AI) tools into educational practices creates new opportunities for teaching and learning. Generative Artificial Intelligence (GenAI) applications have the potential to support personalized learning, improve students' understanding of complex topics, and encourage self-regulated learning [1]. Many students use these tools as academic assistants to clarify difficult concepts, organize study material, prepare for examinations, or support writing tasks [2]. As a result, GenAI tools are becoming part of students' everyday academic activities and are gradually reshaping how learning is approached in higher education [3–5].

At the same time, the increasing use of AI in education raises important concerns. Issues related to academic integrity, the authenticity of student work, and the risk of excessive reliance on automated systems have become central topics of discussion [6]. The ability of GenAI tools to generate ready-made answers and written content challenges traditional assessment practices and raises questions about how educators can ensure that

students remain cognitively and critically engaged with learning tasks rather than using AI-generated outputs as substitutes for their own reasoning and reflection. In this context, the term “passive role” does not suggest that student passivity is a new phenomenon caused by GenAI. Rather, it refers to the possibility that GenAI may reinforce pre-existing tendencies toward surface-level engagement when students rely on generated responses without critically evaluating, revising, contextualizing, or learning from them [7].

The distinction between active and passive learning has long been central to pedagogical theory, with active learning emphasizing students’ cognitive engagement, reflection, application, and knowledge construction rather than the simple reception of ready-made information [8]. In this context, GenAI tools should not be viewed as creating the problem of passive learning, but rather as introducing a new technological setting in which this long-standing pedagogical concern must be reconsidered. When used critically, such tools may support explanation, inquiry, and self-regulated learning; however, when used mainly to obtain ready-made answers, they may reinforce surface-level engagement by reducing students’ need to generate, test, and justify their own reasoning [9]. Therefore, examining how students report using GenAI tools is important for understanding whether these technologies are being integrated as supports for active cognitive engagement or mainly as shortcuts for task completion.

The existing literature shows a growing interest in students’ and educators’ attitudes toward AI, as well as in the pedagogical and ethical implications of its use [10,11]. However, despite this increasing attention, empirical evidence remains limited regarding how students practically use Generative AI tools, how frequently they rely on them, and how they perceive their role in the learning process as stated in the work of Baek et al. [12]. This study aims to contribute to this growing body of research by systematically investigating university students’ reported usage patterns, application contexts, and motivations related to the use of Generative Artificial Intelligence in higher education.

2. Related Work

The rapid expansion of GenAI in higher education has stimulated a growing body of research on how students perceive, adopt, and use such tools in their academic lives. Early discussions often focused on the disruptive potential of ChatGPT and similar systems, particularly with regard to assessment and academic integrity [13,14]. More recent studies, however, have moved beyond general debate and have begun to document concrete patterns of student use, perceived educational benefits, and emerging pedagogical concerns. As noted by Chan and Hu [10], students do not approach GenAI merely as a novel technology, but as a potentially useful learning resource that may support writing, idea generation, research, and individualized assistance. In a similar vein, Ngo [15] showed that students generally perceive ChatGPT as a convenient educational aid, while remaining aware of risks related to inaccuracy, dependence, and superficial learning.

Previous research indicated that students generally hold positive attitudes toward GenAI, while also expressing certain reservations [16,17]. For example, Chan and Hu [10] reported that students recognized important advantages, such as immediate feedback, support for brainstorming, and help with academic tasks, but also expressed concerns about bias, misinformation, privacy, and the possible weakening of independent thinking. Similar conclusions were reached by Almassaad et al. [18], who found that university students associated GenAI tools with improved efficiency and easier access to information, while at the same time identifying ethical and practical challenges, including overreliance and uncertainty regarding appropriate academic use. From a more learning-oriented perspective, Pavlenko and Syzenko [19] reported that students tended to value ChatGPT

mainly as a support tool for clarification, guidance, and understanding academic content, rather than as a replacement for their own learning process.

A related strand of research has examined students' awareness of GenAI tools, their confidence in using them, and the extent to which their experiences differ across academic disciplines [20]. Kelly et al. [2], in one of the earlier large-scale quantitative studies in this area, demonstrated that awareness of generative AI tools among university students was already high, although confidence and intensity of use varied considerably. Their findings suggest that students differ not only in whether they are aware of GenAI tools, but also in how confidently and purposefully they use them for academic work. This distinction is especially relevant because it suggests a shift from simple awareness or occasional experimentation with GenAI tools toward more purposeful academic uses, such as clarifying difficult concepts, summarizing or organizing study material, generating ideas, supporting writing tasks, preparing for examinations, or checking the clarity of one's own understanding. Malmström et al. [21], in their survey of university students in Sweden, also showed that AI-supported learning was becoming increasingly normalized, while students remained attentive to questions of trust, reliability, and the educational implications of machine-generated content.

The literature further indicates that students tend to employ GenAI tools for predominantly pragmatic and academically functional purposes [12,22,23]. Rather than using them primarily for entertainment or creative experimentation, students most often turn to them for information search, concept explanation, summarization, writing assistance, idea generation, language support, and exam preparation [24]. This pattern is clearly reflected in the work of Chatzopoulos [25], who discusses the growing presence of ChatGPT and related tools in university settings and emphasizes their role in reshaping how students search for knowledge, organize academic work, and interact with learning material. In parallel, Ngo [15] showed that students often value ChatGPT because it simplifies difficult content and offers rapid support during the learning process, while Kelly et al. [2] highlighted its growing use as a practical academic assistant across disciplinary contexts. From the findings in [2,15] one can infer that GenAI tools such as ChatGPT, suggest that GenAI is increasingly embedded in students' study routines as a productivity and comprehension aid rather than solely as a text-generation mechanism.

A more specialized body of work has examined the role of GenAI in computing and software engineering education, where students frequently use such systems for coding-related tasks. Kharrufa et al. [26] explored the integration of large language models into software engineering team projects and argued that these tools can take on multiple pedagogical roles, from assistant and explainer to collaborator and productivity enhancer. Likewise, Yabaku and Ouhbi [27] found that students in software engineering generally viewed generative AI tools positively, especially in relation to programming support, efficiency, and problem-solving. At the same time, both studies caution that the educational value of these tools depends on the extent to which students remain cognitively engaged with the underlying reasoning process rather than simply accepting generated outputs. This concern is echoed in the broader review by Reihanian et al. [28], which identifies accuracy, authenticity, and assessment as central challenges in the use of GenAI within computer science education.

Beyond individual empirical studies, recent synthesis work has begun to frame GenAI within wider transformations in university pedagogy [29–31]. To this end, Mavroudi and Wagstaffe [32] suggest that digital transformation in higher education should not be understood only as technological adoption, but as a broader pedagogical shift involving changing roles, expectations, and relationships between teachers, students, and knowledge practices. This perspective is highly relevant to the study of GenAI, as it places student

use of artificial intelligence within a wider landscape of educational change rather than treating it as an isolated phenomenon. In this sense, the adoption of GenAI tools may be interpreted not simply as a matter of convenience, but as part of an ongoing reconfiguration of how academic support, learning autonomy, and knowledge production are experienced in higher education.

Overall, the existing literature points to several broad conclusions. First, student familiarity with GenAI tools has increased rapidly, and the technology is becoming normalized in higher education settings. Second, ChatGPT consistently emerges as the dominant platform, even when students are aware of alternatives such as Gemini, Copilot, Claude, or more specialized systems. Third, the most common uses of GenAI are strongly connected to academic support functions, especially information retrieval, conceptual clarification, writing-related assistance, and study efficiency. Fourth, positive perceptions are consistently accompanied by concerns related to reliability, dependence, authorship, and academic integrity. Finally, while the literature has made important progress in documenting student attitudes and experiences, relatively fewer studies provide detailed empirical evidence on how patterns of GenAI use differ according to demographic or educational variables, or how frequency, motivation, and academic purpose intersect within specific institutional contexts [23,33–35].

It is precisely at this point that the present study seeks to contribute. Building on previous findings mentioned in the aforementioned published literature works, this research examines not only whether students use GenAI tools, but also how frequently they use them, which tools they prefer, for which academic purposes they employ them, and what motivates their engagement. By focusing on a large sample of undergraduate students from a public university and by combining descriptive with correlational analyses, the study aims to provide a more detailed empirical picture of students' attitudes, practices, and perceptions regarding GenAI use in higher education.

Taken together, these studies provide the conceptual and empirical background for the present work, while a selective comparison with representative studies is provided in Section 5 to position the present findings against prior research.

3. Materials and Methods

3.1. Research Questions

This study aims to examine how university students use Generative Artificial Intelligence (GenAI) tools, with a particular focus on their perceptions, usage patterns, and perceived impact on everyday academic activities. To address this aim, the following research questions (RQs) were investigated:

RQ1: What is the frequency and preference of GenAI tool usage (e.g., ChatGPT, Gemini, DeepSeek, Copilot, etc.) among university students across demographics like age, gender, school, academic year and, professional status?

RQ2: How do students utilize GenAI tools in their academic tasks such as task automation, paper and code writing, concept understanding and learning, exam preparation, and personal assistance and what motivates these uses (i.e., productivity, learning, creativity, entertainment)?

3.2. Research Context and Participants

This study was conducted at the University of West Attica (UNIWA) during the period from April to November 2025. The participants were undergraduate students enrolled across all 27 departments and 6 academic schools of the university. The questionnaire was distributed online, and student participation was anonymous and voluntary. A total of 788 undergraduate students completed the questionnaire; 424 (53.8%) were male, 355

(45.1%) were female, and 9 (1.1%) identified as other. Participants were drawn from across the university's 27 departments and 6 academic schools. However, because the questionnaire was distributed electronically and participation was voluntary, the exact number of students who received or viewed the invitation cannot be determined; therefore, a formal response rate cannot be calculated. Accordingly, the sample is treated as a large-scale institutional convenience sample. The findings are therefore interpreted as exploratory evidence of reported GenAI usage patterns within this specific university context, rather than as statistically representative of the entire undergraduate population.

3.3. Instrument Development

The research questionnaire (Table 1) consisted of 51 items to answer the research questions (RQs). It consisted of both closed and open-ended questions. A Likert scale was used by many of the closed-ended questions to quantify responses, and the open-ended descriptive questions were used to express the students' opinions and feelings about the GenAI tools, so plenty of feedback was collected.

Table 1. Research's questionnaire.

Item	Type	Related to
Q1. Gender	Closed-ended	Demographics
Q2. Age	Closed-ended	Demographics
Q3. What school are you studying in	Closed-ended	Demographics
Q4. What department are you studying in?	Closed-ended	Demographics
Q5. What academic year are you in?	Closed-ended	Demographics
Q6. Professional status	Closed-ended	Demographics
Q7. If you work, fill in how many hours you work per week.	Closed-ended	Demographics
Q8. Which of the following Artificial Intelligence (AI) applications do you use? Select the frequency of use.	Questions Q8.1–Q8.11	RQ1
Q8.1 ChatGPT	Likert scale	RQ1
Q8.2 DeepSeek	Likert scale	RQ1
Q8.3 Gemini	Likert scale	RQ1
Q8.4 Claude AI	Likert scale	RQ1
Q8.5 Copilot	Likert scale	RQ1
Q8.6 Perplexity AI	Likert scale	RQ1
Q8.7 Meta AI	Likert scale	RQ1
Q8.8 MidJourney	Likert scale	RQ1
Q8.9 DALL·E 3	Likert scale	RQ1
Q8.10 Cursor	Likert scale	RQ1
Q8.11 Sora	Likert scale	RQ1
Q9. What other AI applications not listed above do you use?	Open-ended	RQ1

Table 1. *Cont.*

Item	Type	Related to
Q10. How often do you generally use Artificial Intelligence (AI) applications in your daily life?	Likert scale	RQ1
Q11. Why do you use Artificial Intelligence (AI) applications?	Questions Q11.A–Q11.F	RQ2
Q11.A. Task automation and productivity	Closed-ended	RQ2
Q11.A1. Information search	Closed-ended	RQ2
Q11.A2. Text writing	Closed-ended	RQ2
Q11.A3. Programming (code assistance, algorithm explanation, code debugging)	Closed-ended	RQ2
Q11.B. Education and learning	Closed-ended	RQ2
Q11.B1. Explaining and understanding difficult concepts in simple terms	Closed-ended	RQ2
Q11.B2. Help with academic work (writing papers, generating ideas and inspiration, gathering study material)	Closed-ended	RQ2
Q11.B3. Exam preparation	Closed-ended	RQ2
Q11.B4. Language assistance (conversation practice, translation, grammar)	Closed-ended	RQ2
Q11.C. Creativity	Closed-ended	RQ2
Q11.C1. Creating or editing images	Closed-ended	RQ2
Q11.C2. Creating or editing videos	Closed-ended	RQ2
Q11.C3. Creating graphics, diagrams, presentations	Closed-ended	RQ2
Q11.D. Entertainment (ideas for stories, discussions, entertaining responses)	Closed-ended	RQ2
Q11.E. Personal assistance and organization	Closed-ended	RQ2
Q11.F. Other	Open-ended	RQ2
Q12. How often do you use Artificial Intelligence (AI) applications when writing your academic papers?	Likert scale	RQ2
Q13. What motivates you to use Artificial Intelligence (AI) tools?	Questions Q13.1–Q13.11	RQ2
Q13.1. To explain and understand difficult concepts	Closed-ended	RQ2
Q13.2 To solve problems, e.g., in mathematics, physics, engineering, etc.	Closed-ended	RQ2
Q13.3. Programming and code writing	Closed-ended	RQ2
Q13.4. Generating and testing ideas, inspiration	Closed-ended	RQ2
Q13.5. Gathering study material	Closed-ended	RQ2

Table 1. *Cont.*

Item	Type	Related to
Q13.6. Writing papers	Closed-ended	RQ2
Q13.7. Searching for sources and bibliography	Closed-ended	RQ2
Q13.8. Creating or editing images	Closed-ended	RQ2
Q13.9. Creating or editing videos	Closed-ended	RQ2
Q13.10. Creating graphics, diagrams, presentations	Closed-ended	RQ2
Q13.11. Other	Open-ended	RQ2

The research instrument (Table 1) consisted of three parts: (i) the demographic data (gender, age, educational status, professional status), (ii) questions about the use (frequency, preference) of GenAI tools by the students related to RQ1, and (iii) questions about the GenAI tool utilization and motivation related to RQ2.

The questionnaire was developed as a purpose-built exploratory instrument designed to map students' reported GenAI usage patterns, preferred tools, application contexts, and motivations. It was not intended to function as a psychometric scale measuring latent constructs such as technology acceptance, perceived usefulness, perceived ease of use, or attitudes toward GenAI. Accordingly, the items were organized according to the study's research questions rather than adapted from a single validated theoretical model such as TAM or UTAUT. The questionnaire mainly included categorical, checklist-type, and purpose-specific items. Therefore, several parts of the instrument captured distinct tools, uses, and motivations rather than repeated indicators of a single underlying construct. For this reason, reliability coefficients such as Cronbach's alpha were not considered appropriate for all item groups. This methodological choice is acknowledged as a limitation of the study.

A 5-point (from 1 to 5) and 3-point (from 1 to 3) Likert scale were used to measure most of the research items, including:

- Q8.1–Q8.11, were measured with a 5-point Likert scale where 1 was “Not at all—I don't know”, 2 was “A little”, 3 was “Moderate”, 4 was “Quite a lot”, and 5 was “A lot”,
- Q10 was measured with a 5-point Likert scale, where 1 was “Not at all”, 2 was “A little”, 3 was “Moderate”, 4 was “Very often”, and 5 was “Too much”,
- Q12, had a slightly different 5-point scale whose answers were more relevant to these questions.

The full research instrument is presented below in Table 1.

3.4. Data Collection

The research's data collection was conducted via an electronic online questionnaire form built with the Microsoft Forms application, which is in accordance with European Law's GDPR regulation. Before filling it, the students had to give their consent via this form. The form did not collect any personal data of the students, as it complied with the GDPR regulation of the European Union. The researchers did not have access to the students IP addresses or other data that could reveal them; moreover, the participants answers were not visible to others. For the statistical analysis of the research data, the statistical software Jamovi version 2.7.18.0 was used, which is open-source and free [36,37].

Because not all participants answered every demographic item, analyses were conducted using the valid responses available for the variables included in each test. Therefore, the valid sample size may differ slightly across tables. The total sample was $N = 788$, while analyses involving university school used $N = 781$ because seven respondents did not provide a valid school response. Where subgroup exclusions were applied, such as the exclusion of the small “Other” gender group from the male/female inferential comparison, the valid N is reported in the corresponding table.

3.5. Research Ethics, Methodological Considerations, and Scope of Interpretation

This study was conducted in accordance with the principles of the Declaration of Helsinki and with applicable data protection requirements. Ethical approval for the study was obtained from the Research Ethics Committee of the University of West Attica prior to data collection (Protocol No. 5112/25-01-2024). All participants were informed about the purpose of the study and provided electronic informed consent before completing the questionnaire. Data were collected through an anonymous online questionnaire administered via Microsoft Forms. Prior to participation, students were informed about the purpose of the study and provided their consent electronically. No personally identifiable information was collected, and the researchers did not have access to IP addresses or other data that could directly reveal participants’ identities. The handling and storage of the data were carried out in a manner consistent with the relevant data protection framework.

At the same time, certain methodological considerations should be taken into account when interpreting the findings. First, the study was conducted within a single public university in Greece. Although the sample size was substantial and included students from multiple departments and schools, the institutional specificity of the sample inevitably limits the extent to which the findings can be generalized to other higher education settings, disciplinary environments, or national contexts. In addition, the distribution of respondents across schools was uneven, with a stronger representation from Engineering-related disciplines, and this should be considered when interpreting the broader patterns observed.

Second, the study relied on self-reported questionnaire data. As in most survey-based research, the findings rely on participants’ self-reported practices, perceptions, and motivations, and therefore reflect stated rather than directly observed behaviour [38]. It is therefore possible that some responses were influenced by recall bias, subjective interpretation of questionnaire items, or a tendency to present one’s practices in a more socially acceptable way. The anonymous and voluntary design of the survey was intended to support more candid responses, but such sources of response bias cannot be fully excluded.

The small number of respondents identifying as “Other” in terms of gender ($n = 9$) limited meaningful subgroup analysis. Therefore, gender-based inferential comparisons were restricted to male and female respondents, and future studies should include larger gender-diverse samples.

Third, the mode of questionnaire distribution may also have influenced participation. The survey was circulated electronically through institutional academic email, which may have affected its visibility among students and may have introduced a degree of self-selection into the final sample. Moreover, while the questionnaire was designed to capture a broad range of practices and perceptions regarding GenAI use, its length may have contributed to response fatigue for some participants. These issues do not invalidate the results, but they should be acknowledged as part of the practical conditions under which the data were collected.

Fourth, the questionnaire was developed as a purpose-built exploratory instrument for mapping students’ reported GenAI usage patterns, preferred tools, application contexts, and motivations. It was not designed as a psychometric scale for measuring latent

constructs such as technology acceptance, perceived usefulness, perceived ease of use, or attitudes toward GenAI. Therefore, although the instrument was aligned with the study's research questions, it was not subjected to full psychometric validation through pilot testing, exploratory factor analysis, or internal consistency assessment. This should be considered when interpreting the findings, which are best understood as descriptive and exploratory evidence rather than as results derived from a validated attitude or acceptance scale. Future research should build on this exploratory instrument by incorporating expert review, pilot testing, and psychometric validation procedures where the aim is to measure latent constructs or develop a reusable scale.

In addition, some Likert-scale responses were recoded into binary use/non-use categories to provide a simplified overview of GenAI tool adoption. Although this approach supported descriptive clarity, it reduced the granularity of the original ordinal data and limited the interpretive value of subsequent association tests. Future studies should retain the full ordinal structure of such responses and apply non-parametric or ordinal modelling approaches, such as Mann–Whitney U tests, Kruskal–Wallis tests, or ordinal logistic regression, to examine differences in GenAI-use intensity more precisely.

Furthermore, several subgroup association tests were conducted across demographic and educational variables. These analyses were exploratory and non-confirmatory. No formal correction for multiple comparisons, such as Holm or false discovery rate adjustment, was applied. Therefore, the reported *p*-values should be interpreted cautiously, especially where they are marginal and accompanied by weak or negligible effect sizes. For this reason, the manuscript does not treat these subgroup tests as confirmatory evidence of group differences, but as descriptive indications that may guide future research. Interpretation is based primarily on effect sizes, practical significance, and consistency with the descriptive patterns rather than on statistical significance alone.

Furthermore, the statistical analysis was primarily based on descriptive statistics and exploratory pairwise association tests. This approach was suitable for mapping broad patterns of GenAI use across the surveyed sample. However, it does not account for the simultaneous influence of multiple demographic, educational, or employment-related variables on the same outcome. More advanced multivariable approaches, such as ordinal regression or mixed-effects modelling, could provide a more integrated analysis of how several predictors jointly relate to GenAI-use frequency or application patterns. Future studies should therefore consider such models, especially when using the full ordinal structure of the data and more balanced samples across academic fields.

Finally, the study adopted a cross-sectional design and therefore captures student attitudes and practices at a specific moment in time. Given the rapid evolution of GenAI tools and their expanding presence in higher education, patterns of use, perceived benefits, and associated concerns may change considerably over relatively short periods. The present findings should therefore be understood as a structured empirical snapshot of an evolving educational landscape rather than as a fixed account of long-term student behaviour.

4. Results

4.1. Demographic Profile

The demographic profile of the respondents is summarized in this section. Gender distribution is reported in Section 3.2, while Figure 1 and Table 2 present its relationship with age groups. This gender distribution is broadly consistent with national patterns observed in Greek tertiary education [39].

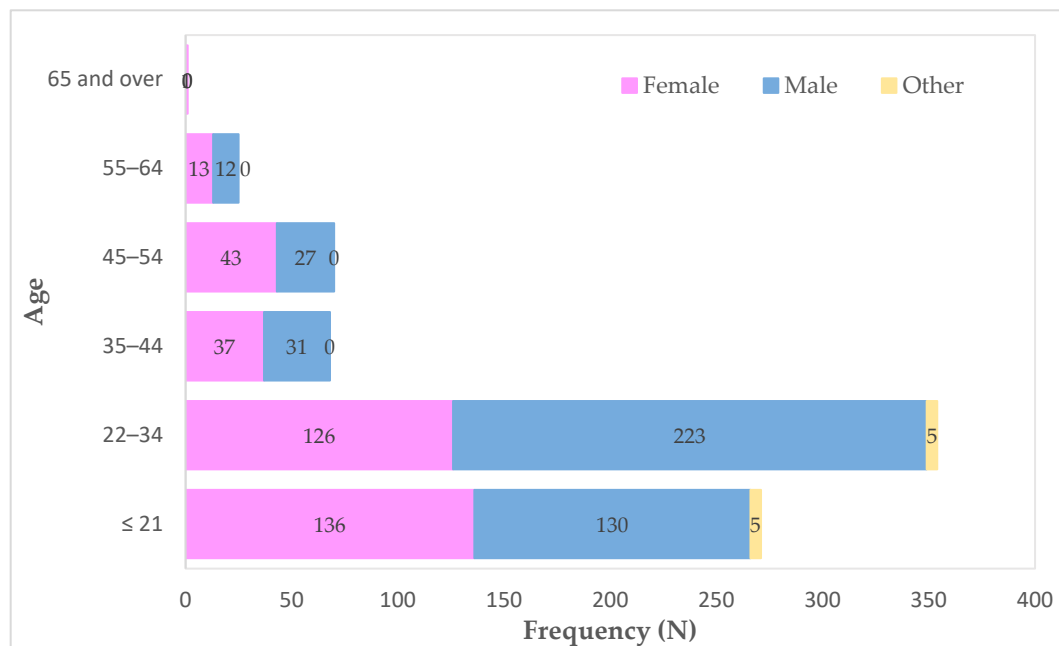


Figure 1. Distribution of participants' age groups by gender (N = 788).

Table 2. Frequencies of Gender (Q1) split by Age (Q2).

1. Gender	2. Age	Counts	% of Total	Cumulative %
Female	less or equal to 21	136	17.3%	17.3%
	22-34	126	16.0%	33.2%
	35-44	37	4.7%	37.9%
	45-54	43	5.5%	43.4%
	55-64	13	1.6%	45.1%
	65 and over	0	0.0%	45.1%
Male	less or equal to 21	130	16.5%	61.5%
	22-34	223	28.3%	89.8%
	35-44	31	3.9%	93.8%
	45-54	27	3.4%	97.2%
	55-64	12	1.5%	98.7%
	65 and over	1	0.1%	98.9%
Other	less or equal to 21	4	0.5%	99.4%
	22-34	5	0.6%	100.0%
	35-44	0	0.0%	100.0%
	45-54	0	0.0%	100.0%
	55-64	0	0.0%	100.0%
	65 and over	0	0.0%	100.0%

Most participants ages were under 34 years of age. Specifically, 270 (34.3%) students were less or equal to 21 years old, 354 (44.9%) were between 22 and 34, 68 (8.6%) were between 35 and 44, 70 (8.9%) were between 45 and 54, 25 (3.2%) were between 55 and 64, and only 1 (0.1%) student was 65 and over, which is a normal distribution for undergraduate students. The presence of students over 30 years of age is not unusual in the Greek higher education system. Undergraduate cohorts may include older students due to delayed university entry, extended study duration, examination retakes, interruptions in study, return to education after employment, or participation in higher education alongside work and family responsibilities. Because age was collected in predefined age categories rather than as exact numerical values, descriptive statistics such as mean, standard deviation,

median, and quartiles could not be calculated with precision. Instead, an exploratory categorical age profile is reported. The largest group of respondents was aged 22–34 years (44.9%, $n = 354$), followed by students aged ≤ 21 years (34.3%, $n = 270$). Smaller proportions were observed in the 35–44 years (8.6%, $n = 68$), 45–54 years (8.9%, $n = 70$), 55–64 years (3.2%, $n = 25$), and ≥ 65 years (0.1%, $n = 1$) categories. Thus, 79.2% of the respondents were aged 34 years or younger, while 20.8% were aged 35 years or older. Figure 1 depicts the age distribution of participants by gender and Table 2 presents the frequencies of the students' gender split by their age.

Valid school information was available for 781 respondents. These students were distributed across 27 university departments and 6 schools of UNIWA as follows: all of these students are distributed across 27 university departments and 6 schools of the UNIWA, in particular: School of Public Health 27 (3.5%), School of Administrative, Economics & Social Sciences 101 (12.9%), School of Food Sciences 13 (1.7%), School of Health & Care Sciences 76 (9.7%), School of Applied Arts & Culture 66 (8.5%), and School of Engineering 498 (63.8%). The six schools represent a broad range of undergraduate study areas within the university. The School of Engineering includes technology- and engineering-oriented programs; the School of Administrative, Economics and Social Sciences includes programs related to management, economics, and social sciences; the School of Health and Care Sciences includes health-related undergraduate programs; the School of Applied Arts and Culture includes programs related to design, arts, and cultural studies; the School of Public Health includes public-health-oriented programs; and the School of Food Sciences includes food science and related applied programs. Therefore, although the sample was strongly weighted toward Engineering students, the respondents were drawn from a range of academic fields, including engineering, health, social sciences, arts/culture, public health, and food sciences. This distribution indicates a strong overrepresentation of Engineering students in the final sample. As a result, the overall findings may reflect, to some extent, the academic culture, digital familiarity, and technology-oriented profile of Engineering-related disciplines. Therefore, school-level comparisons and general interpretations of GenAI adoption should be read with this disciplinary imbalance in mind. Table 3 presents the frequencies of the students' schools split by gender.

This research has highlighted that about half of the students, 416 (52.8%), are employed, while 372 (47.2%) are unemployed. Regarding the working hours about the half of the students, 221 (53.4%) have a full-time job, 71 (17.1%) work reduced (20–34) hours, 66 (15.9%), work part-time (less than 20 h), 37 (8.9%), work overtime (41–50 h), and the rest of them 19 (4.6%), are of high workload. Table 4 presents the frequencies of students' professional status, and Table 5 presents the frequencies of students' working hours. Given the number of subgroup association tests conducted and the absence of formal multiple-comparison correction, these results should be interpreted as exploratory and non-confirmatory; marginal p -values are not treated as strong evidence of substantive group differences.

4.2. Students' Usage of GenAI Tools

To address the first research question (RQ1), responses to items Q8.1–Q8.11 were first summarized descriptively using their original 5-point response categories. For an additional broad overview of whether participants reported any use of the listed GenAI tools, the responses were also recoded into a binary variable. Specifically, the response option “Not at all—I do not know” was classified as “No”, whereas the options “A little”, “Moderate”, “Quite a lot”, and “A lot” were classified as indicating some level of reported use. This binary recoding should not be interpreted as a measure of intensity or regular adoption, because it groups occasional and frequent users together. It was used only to

provide a simplified descriptive indicator of whether respondents reported any degree of engagement with at least one listed GenAI tool. The full ordinal distribution of responses is retained and presented in Figure 2 and Table 6, and these 5-point results should be used when interpreting differences in intensity of use. Based on this broad “any reported use” indicator, 766 students (97.2%) reported at least some use of one or more listed GenAI tools, while 22 students (2.8%) reported no use or no awareness of the listed tools.

Table 3. Distribution of students across university schools by gender (valid $N = 781$) (Q2, Q4).

4. What School Are You Studying at	1. Gender	Counts	% of Total	Cumulative %
School of Public Health	Female	20	2.6%	2.6%
	Male	6	0.8%	3.3%
	Other	1	0.1%	3.5%
School of Administrative, Economics & Social Sciences	Female	76	9.7%	13.2%
	Male	24	3.1%	16.3%
	Other	1	0.1%	16.4%
School of Food Sciences	Female	11	1.4%	17.8%
	Male	2	0.3%	18.1%
	Other	0	0.0%	18.1%
School of Health & Care Sciences	Female	61	7.8%	25.9%
	Male	15	1.9%	27.8%
	Other	0	0.0%	27.8%
School of Applied Arts & Culture	Female	53	6.8%	34.6%
	Male	12	1.5%	36.1%
	Other	1	0.1%	36.2%
School of Engineering	Female	133	17.0%	53.3%
	Male	359	46.0%	99.2%
	Other	6	0.8%	100.0%

Table 4. Frequencies of students’ professional status (Q6).

6. Professional Status	Counts	% of Total	Cumulative %
Employed	416	52.8%	52.8%
Unemployed	372	47.2%	100.0%

Table 5. Frequencies of students’ working hours (Q7).

7. If You Work, Fill in How Many Hours You Work per Week.	Counts	% of Total	Cumulative %
20–34 h (Reduced hours)	71	17.1%	17.1%
35–40 h (Full-time—Standard)	221	53.4%	70.5%
41–50 h (Overtime)	37	8.9%	79.5%
Less than 20 h (Part-time)	66	15.9%	95.4%
More than 50 h (High workload)	19	4.6%	100.0%

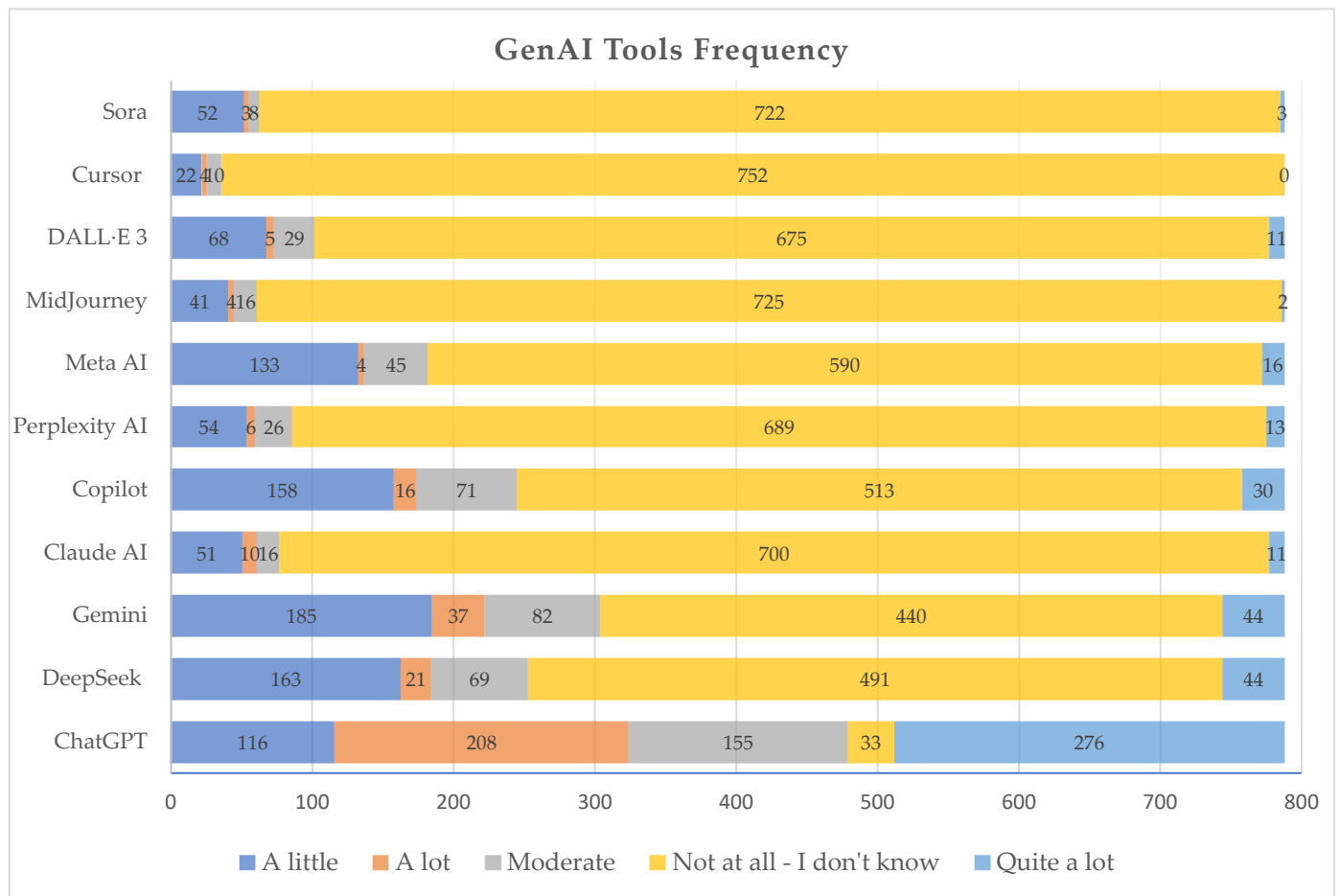


Figure 2. Distribution of students' self-reported frequency of GenAI tool use.

Table 6. Frequencies of GenAI tool usage by the students (Q8.1–Q8.11).

8.1 ChatGPT	Counts	% of Total	Cumulative %
A little	116	14.7%	14.7%
A lot	208	26.4%	41.1%
Moderate	155	19.7%	60.8%
Not at all—I don't know	33	4.2%	65.0%
Quite a lot	276	35.0%	100.0%
8.2 DeepSeek	Counts	% of Total	Cumulative %
A little	163	20.7%	20.7%
A lot	21	2.7%	23.4%
Moderate	69	8.8%	32.1%
Not at all—I don't know	491	62.3%	94.4%
Quite a lot	44	5.6%	100.0%
8.3 Gemini	Counts	% of Total	Cumulative %
A little	185	23.5%	23.5%
A lot	37	4.7%	28.2%
Moderate	82	10.4%	38.6%
Not at all—I don't know	440	55.8%	94.4%
Quite a lot	44	5.6%	100.0%

Table 6. Cont.

8.4 Claude AI	Counts	% of Total	Cumulative %
A little	51	6.5%	6.5%
A lot	10	1.3%	7.7%
Moderate	16	2.0%	9.8%
Not at all—I don't know	700	88.8%	98.6%
Quite a lot	11	1.4%	100.0%
8.5 Copilot	Counts	% of Total	Cumulative %
A little	158	20.1%	20.1%
A lot	16	2.0%	22.1%
Moderate	71	9.0%	31.1%
Not at all—I don't know	513	65.1%	96.2%
Quite a lot	30	3.8%	100.0%
8.6 Perplexity AI	Counts	% of Total	Cumulative %
A little	54	6.9%	6.9%
A lot	6	0.8%	7.6%
Moderate	26	3.3%	10.9%
Not at all—I don't know	689	87.4%	98.4%
Quite a lot	13	1.6%	100.0%
8.7 Meta AI	Counts	% of Total	Cumulative %
A little	133	16.9%	16.9%
A lot	4	0.5%	17.4%
Moderate	45	5.7%	23.1%
Not at all—I don't know	590	74.9%	98.0%
Quite a lot	16	2.0%	100.0%
8.8 MidJourney	Counts	% of Total	Cumulative %
A little	41	5.2%	5.2%
A lot	4	0.5%	5.7%
Moderate	16	2.0%	7.7%
Not at all—I don't know	725	92.0%	99.7%
Quite a lot	2	0.3%	100.0%
8.9 DALL·E 3	Counts	% of Total	Cumulative %
A little	68	8.6%	8.6%
A lot	5	0.6%	9.3%
Moderate	29	3.7%	12.9%
Not at all—I don't know	675	85.7%	98.6%
Quite a lot	11	1.4%	100.0%
8.10 Cursor	Counts	% of Total	Cumulative %
A little	22	2.8%	2.8%
A lot	4	0.5%	3.3%
Moderate	10	1.3%	4.6%
Not at all—I don't know	752	95.4%	100.0%
8.11 Sora	Counts	% of Total	Cumulative %
A little	52	6.6%	6.6%
A lot	3	0.4%	7.0%
Moderate	8	1.0%	8.0%
Not at all—I don't know	722	91.6%	99.6%
Quite a lot	3	0.4%	100.0%

ChatGPT remains students' first choice (Yes: 95.8%, $n = 755$; No: 4.2%, $n = 33$), followed by Gemini (Yes: 44.2%, $n = 348$; No: 55.8%, $n = 440$), DeepSeek (Yes: 37.7%, $n = 297$; No:

62.3%, $n = 491$), and Copilot (Yes: 34.9%, $n = 275$; No: 65.1%, $n = 513$). About one quarter of the students use Meta AI (Yes: 25.1%, $n = 198$; No: 74.9%, $n = 590$), while smaller percentages use DALL·E (Yes: 14.3%, $n = 113$; No: 85.7%, $n = 675$), Perplexity AI (Yes: 12.6%, $n = 99$; No: 87.4%, $n = 689$), and Claude AI (Yes: 11.2%, $n = 88$; No: 88.8%, $n = 700$). Sora (Yes: 8.4%, $n = 66$; No: 91.6%, $n = 722$), MidJourney (Yes: 8.0%, $n = 63$; No: 92.0%, $n = 725$), and Cursor (Yes: 4.6%, $n = 36$; No: 95.4%, $n = 752$) appear at the bottom of the ranking, which may reflect their more specialized orientation compared with general-purpose conversational AI tools. This pattern is consistent with recent student-focused studies showing that ChatGPT remains the dominant GenAI tool in higher education, while other tools are used by smaller or more task-specific groups of students [10,40,41]. The frequency of GenAI tool use is visualized in Figure 2, while the exact frequencies and percentages are reported in Table 6 to support numerical transparency and allow more detailed interpretation of the distribution across response categories.

Because this binary variable collapses different levels of use intensity, the following subgroup analyses based on it are interpreted only as exploratory comparisons of broad reported use/non-use patterns. Next, the relationship between GenAI tool use and key demographic variables, including gender, school of study, professional status, and age, was examined. For this purpose, a chi-square test of independence (or association) was initially performed to determine if students' gender and the use of GenAI tools are independent or associated with one another. Therefore, the hypothesis was [42]:

H₁. *Use of GenAI tools is independent of gender (no association).*

H₂. *Use of GenAI tools is related to gender.*

At the first stage, the following chi-square test's assumptions were tested: (i) expected frequencies had to be sufficiently large (>5), and (ii) data had to be independent of one another. However, the expected-frequency assumption was not met because of the very small number of respondents identifying as "Other" in terms of gender ($n = 9$). Therefore, this subgroup was excluded from the male/female inferential comparison to avoid low expected cell frequencies. This exclusion was applied only to the gender-based association test and is acknowledged as a limitation of the study. Due to the very small size of the "Other" gender group ($n = 9$), no reliable inferential comparison could be conducted for this subgroup. Therefore, the exclusion of this group from the gender-based association test should be interpreted as a statistical limitation rather than as an indication that this group was analytically unimportant. Future studies with larger and more balanced gender-diverse samples should examine whether GenAI usage patterns differ among students identifying outside the male/female categories. A new chi-square test of independence was conducted to examine whether the use of GenAI tools was related to gender (Male vs. Female). The test revealed no statistically significant association between gender and GenAI tool usage, $\chi^2(1) = 0.74$, $p = 0.389$ (Table 7). The effect size was negligible, as indicated by Cramér's $V = 0.03$. Therefore, there is no evidence that the use of GenAI tools was related to gender. Both male and female participants use GenAI tools at nearly identical, very high rates.

It was then assessed whether GenAI tool use was associated with the participants' school of study. The hypothesis was [42]:

H₃. *Use of GenAI tools is independent of the school of study (no association).*

H₄. *Use of GenAI tools is related to the school of study.*

Table 7. χ^2 Test of Association between GenAI use and gender, excluding the “Other” gender group due to small subgroup size (valid $N = 779$).

8. Do You Use GenAI Tools?			
1. Gender	Yes	No	Total
Female	345	10	355
Male	416	8	424
Total	761	18	779
χ^2 Tests			
	Value	df	p
χ^2	0.741	1	0.389
N	779		
Nominal			
	Value		
Phi-coefficient	0.0308		
Cramer's V	0.0308		

The chi-square test's assumptions were tested, and found that the first assumption (Expected frequencies > 5) was not met. Therefore, Fisher's Exact test was used, where any expected cell frequency can be less than 5 [42]. Fisher's Exact Test (Freeman-Halton extension for 6×2 tables) was conducted to examine whether the use of GenAI tools was related to the school of study of the participants across all six school groups. The analysis indicated that GenAI tool usage was not significant associated with students' school of study ($p = 0.503$), while the effect size remained negligible (Cramér's $V = 0.07$; Table 8). So, there is no evidence that GenAI tool usage was related to the school a student belongs to. The broad use/non-use indicator was high across all six schools. Therefore, the null hypothesis that GenAI tool usage is independent of studying school cannot be rejected ($p = 0.503$).

Table 8. Fisher's Exact Test for the relationship between GenAI tool use and participants' university school (valid $N = 781$).

8. Do You Use GenAI Tools?			
3. What School Are You Studying at	Yes	No	Total
School of Engineering	486	12	498
School of Applied Arts & Culture	63	3	66
School of Health & Care Sciences	72	4	76
School of Administrative, Economics & Social Sciences	99	2	101
School of Food Sciences	13	0	13
School of Public Health	26	1	27
Total	759	22	781
χ^2 Tests			
	Value	p	
Fisher's exact test		0.503	
N	781		
Nominal			
	Value		
Phi-coefficient	NaN		
Cramer's V	0.0659		

Next, the association between GenAI tool use and participants' professional status was assessed. A chi-square test of independence was conducted to examine whether the broad use/non-use indicator was related to participants' professional status. The uncorrected test suggested a possible association between professional status and GenAI tool usage, $\chi^2(1) = 3.99$, $p = 0.046$. However, the effect size was negligible (Cramér's $V = 0.07$; Table 9), indicating limited practical significance. Employed participants reported some level of GenAI tool use at a rate of 98.32%, compared to 95.97% among unemployed participants, a difference of only 2.35 percentage points. Given the exploratory nature of the subgroup analyses and the absence of multiple-comparison correction, this result should be interpreted cautiously and should not be treated as confirmatory evidence of a substantive difference between employed and unemployed students.

Table 9. χ^2 Test of Association between GenAI use and professional status (valid $N = 788$).

8. Do You Use GenAI Tools?			
6. Professional Status	Yes	No	Total
Employed	409	7	416
Unemployed	357	15	372
Total	766	22	788
χ^2 Tests			
	Value	df	<i>p</i>
χ^2	3.99	1	0.046
N	788		
Nominal			
	Value		
Phi-coefficient	0.0712		
Cramer's V	0.0712		

Finally, GenAI tool use was analyzed in relation to the participants' age. Because the assumptions of the chi-square test were not satisfied (expected frequencies > 5), Fisher's Exact test (Freeman–Halton extension for 6×2 tables) was applied. No statistically significant association between age and GenAI tool usage was observed ($p = 0.319$) and the effect size was negligible (Cramér's $V = 0.08$; Table 10). GenAI tool usage showed no meaningful variation across age groups. Adoption rates were consistently high across all age groups, with usage rates exceeding 95% in each group. This finding suggests that, within the present sample, age did not substantially differentiate whether students used GenAI tools. Rather, the near-saturation of basic adoption may indicate that GenAI use has become broadly normalized among undergraduate respondents. This interpretation is broadly consistent with recent student-focused studies showing high levels of awareness and use of GenAI tools in higher education, although some studies suggest that age may still influence frequency, confidence, or type of use rather than simple adoption/non-adoption [43,44]. The null hypothesis that GenAI tool usage is independent of age cannot be rejected ($p = 0.319$). Additionally, the "65 and over" group included only one participant, rendering any statistical interpretation for this group unreliable.

Overall, the association tests based on the binary use/non-use variable should be interpreted as exploratory. Because the recoded variable distinguishes only between participants reporting some degree of use and those reporting no use or no awareness, it does not capture differences in the intensity of GenAI tool use. Consequently, these tests provide limited explanatory depth and should be understood as a broad indication of adoption patterns rather than as a detailed analysis of usage frequency.

Table 10. Fisher’s Exact Test: Does the use of GenAI tools is related to participants age?

8. Do You Use GenAI Tools?			
2. Age	Yes	No	Total
less or equal to 21	258	12	270
22–34	348	6	354
35–44	66	2	68
45–54	68	2	70
55–64	25	0	25
65 and over	1	0	1
Total	766	22	788
χ^2 Tests			
	Value	<i>p</i>	
Fisher’s exact test		0.319	
N	788		
Nominal			
	Value		
Phi-coefficient	NaN		
Cramer’s V	0.0800		

These pairwise analyses should be interpreted as exploratory and descriptive; they identify possible associations between individual variables and GenAI-use patterns but do not model the combined influence of multiple predictors.

4.3. Frequency of GenAI Tool Use Among Students

Another question examined in this study is the frequency with which students use GenAI tools in their daily lives. To this end, the responses to Question Q10 were analyzed. The results in Table 11 reveal a heterogeneous pattern of frequency of use: while a large group of students (31.5%, $n = 248$) reported using these tools very often, approximately several times per week, the second largest group (28.2%, $n = 222$) reported more occasional use, corresponding to a few times per month. In addition, 24.7% of students ($n = 195$) were heavy users, reporting daily or almost daily use, whereas 12.1% ($n = 95$) reported rare use and only 3.6% ($n = 28$) reported no use at all. These findings indicate that although GenAI use is widespread among respondents, the intensity of use varies considerably. The present questionnaire did not directly examine the reasons for more frequent or less frequent use, such as subscription costs, availability of free versions, accessibility, perceived need, digital confidence, or discipline-specific requirements. Therefore, these factors should be examined in future research to better explain differences in frequency of GenAI adoption.

Table 11. Frequencies of how often you generally use AI tools in your daily life.

10. How Often Do You Generally Use Artificial Intelligence (AI) Applications in Your Daily Life?	Counts	% of Total	Cumulative %
A little (once a month or less)	95	12.1%	12.1%
Moderate (a few times a month)	222	28.2%	40.2%
Not at all	28	3.6%	43.8%
Too much (daily or almost daily)	195	24.7%	68.5%
Very often (several times a week)	248	31.5%	100.0%

Next, the association between the frequency of GenAI tool use and participants’ gender was examined. For this purpose, a chi-square test of independence was conducted to assess

whether the frequency of AI application use in daily life is related to gender. The test revealed a statistically significant association between gender and AI usage frequency, $\chi^2(4) = 13.9, p = 0.008$. The effect size was small, Cramér's $V = 0.133$ (Table 12). The results indicate that male and female participants differ in how frequently they use AI applications in their daily lives. Examining the observed vs. expected frequencies reveals the direction of this difference: Female participants were observed more often than expected in the moderate-use category (117 observed vs. 100.7 expected) and in the non-use category (14 observed vs. 10.5 expected), suggesting a tendency toward lower-frequency use. Male participants were observed more often than expected in the daily or almost daily use category (121 observed vs. 105.6 expected) and in the several-times-per-week category (143 observed vs. 134.4 expected), suggesting a tendency toward higher-frequency use. In other words, male respondents appeared more concentrated in higher-frequency AI-use categories, whereas female respondents were more concentrated in moderate or lower-use categories. However, the effect size was small (Cramér's $V = 0.133$), indicating that gender explains only a modest portion of the variation in AI usage frequency. Therefore, these findings should not be interpreted as evidence of AI dependency among male students. Rather, they suggest that gender-related differences in intensity of use may deserve further investigation, particularly in relation to digital confidence, disciplinary context, perceived usefulness, academic workload, and possible risks of overreliance [45,46]. Future research should examine whether higher-frequency GenAI use among specific student groups reflects productive integration into academic practice, greater digital confidence, discipline-related needs, or possible forms of overreliance that cannot be inferred from frequency data alone.

Table 12. χ^2 Test of Association between the frequency of daily life GenAI usage and Gender.

		Gender (Male—Female)		
10. How Often Do You Generally Use Artificial Intelligence (AI) Applications in Your Daily Life?		Female	Male	Total
A little (once a month or less)	Observed	47	47	94
	Expected	42.8	51.2	94.0
Moderate (a few times a month)	Observed	117	104	221
	Expected	100.7	120.3	221.0
Not at all	Observed	14	9	23
	Expected	10.5	12.5	23.0
Too much (daily or almost daily)	Observed	73	121	194
	Expected	88.4	105.6	194.0
Very often (several times a week)	Observed	104	143	247
	Expected	112.6	134.4	247.0
Total	Observed	355	424	779
	Expected	355	424	779
χ^2 Tests				
	Value	df	<i>p</i>	
χ^2	13.9	4	0.008	
N	779			
Nominal				
	Value			
Phi-coefficient	NaN			
Cramer’s V	0.133			

The above finding sparked the researchers' interest to examine if other relations happened, such as:

- Whether the use of the GenAI tools was related to the professional status and the working hours of the participants.
- Whether the use of the GenAI tools was related to the participants' school.
- Whether the use of the GenAI tools was related to the participants' academic year.

A chi-square test of independence was performed to examine the relationship between participants' professional status (employed vs. unemployed) and the frequency of their GenAI use (Table 13). The uncorrected analysis suggested a possible association between professional status and frequency of GenAI use, $\chi^2(4) = 10.3$, $p = 0.036$. Unemployed participants were more likely to report using AI "a little" or "not at all" compared with employed participants. However, the strength of the association was weak (Cramér's $V = 0.114$). Therefore, this result should be interpreted cautiously and not as confirmatory evidence of a substantive group difference, particularly given the exploratory nature of the subgroup analyses and the absence of multiple-comparison correction.

Table 13. χ^2 Test of Association between the frequency of daily life GenAI usage and the professional status of the participants.

		6. Professional Status		
10. How Often Do You Generally Use Artificial Intelligence (AI) Applications in Your Daily Life?		Employed	Unemployed	Total
A little (once a month or less)	Observed	41	54	95
	Expected	50.2	44.8	95.0
Moderate (a few times a month)	Observed	123	99	222
	Expected	117.2	104.8	222.0
Not at all	Observed	9	19	28
	Expected	14.8	13.2	28.0
Too much (daily or almost daily)	Observed	111	84	195
	Expected	102.9	92.1	195.0
Very often (several times a week)	Observed	132	116	248
	Expected	130.9	117.1	248.0
Total	Observed	416	372	788
	Expected	416	372	788
χ^2 Tests				
	Value	df	p	
χ^2	10.3	4	0.036	
N	788			
Nominal				
	Value			
Phi-coefficient	NaN			
Cramer's V	0.114			

To further explore the relationship between AI use and employment status, the frequency of GenAI tool use was analyzed in relation to participants' working hours. Initially, the suitability of a chi-square test of independence was assessed; however, because some expected frequencies were below 5, Fisher's Exact test using the Freeman–Halton extension for 5×5 tables was applied instead. The test indicated only a marginal association between frequency of GenAI tool use and participants' working hours ($p = 0.0492$), while the corresponding effect size was very small (Cramér's $V = 0.09$; Table 14), indicating a negligible practical relationship between the variables. Therefore, although recent workplace-focused

studies show that GenAI adoption can be associated with productivity, task support, and organizational workflow integration, the present findings suggest that working hours alone did not meaningfully differentiate students' frequency of GenAI use. This may be because the study did not measure the type of employment, whether participants used GenAI at work, whether their workplace encouraged AI adoption, or whether their tasks were suitable for AI-assisted support [47–49]. Consequently, the result should be interpreted cautiously as evidence that the quantity of working hours, by itself, was not a strong differentiating factor within this student sample.

Table 14. Fisher's Exact Test for the relationship between frequency of GenAI tool use and working hours among employed respondents with valid working-hours data (valid $N = 413$).

7. If You Work, Fill in How Many Hours You Work per Week						
10. How Often Do You Generally Use Artificial Intelligence (AI) Applications in Your Daily Life?	20–34 h (Reduced Hours)	35–40 h (Full-Time—Standard)	41–50 h (Overtime)	Less than 20 h (Part-Time)	More than 50 h (High Workload)	Total
Not at all	1	5	2	1	0	9
A little (once a month or less)	7	23	5	4	2	41
Moderate (a few times a month)	23	70	5	18	6	122
Very often (several times a week)	25	64	16	22	3	130
Too much (daily or almost daily)	15	59	9	20	8	111
Total	71	221	37	65	19	413
χ^2 Tests						
	Value	p				
Fisher's exact test		0.492				
N	413					
Monte Carlo simulation						
Nominal						
	Value					
Phi-coefficient	NaN					
Cramer's V	0.0946					

Next, it was examined whether the frequency of GenAI tool use was related to participants' university school. Fisher's Exact test was used because the assumptions of the chi-square test of independence were not fully met. The uncorrected analysis suggested a possible association between university school and frequency of GenAI tool use ($p = 0.013$). However, the effect size was weak (Cramér's $V = 0.105$; Table 15), and the result should be interpreted as exploratory rather than confirmatory. Although the School of Engineering represented the largest subgroup in the sample ($N = 498$), which may have influenced the overall distribution, the findings suggest only limited school-level differentiation in GenAI-use frequency. Rather than indicating a strong disciplinary effect, the results are better understood as showing that frequent GenAI use was broadly present across the surveyed schools, with some descriptive variation between them. This interpretation is consistent with recent higher education studies reporting widespread student adoption of

GenAI tools, while also noting that frequency, attitudes, and use cases may vary by field of study or disciplinary context [50,51].

Table 15. Fisher’s Exact Test for the relationship between frequency of GenAI tool use and participants’ university school (valid $N = 781$).

3. What School Are You Studying at.							
10. How Often Do You Generally Use Artificial Intelligence (AI) Applications in Your Daily Life?	School of Engineering	School of Applied Arts & Culture	School of Health & Care Sciences	School of Administrative, Economics & Social Sciences	School of Food Sciences	School of Public Health	Total
Not at all	13	5	5	4	0	1	28
A little (once a month or less)	51	11	12	15	0	6	95
Moderate (a few times a month)	132	20	29	29	3	9	222
Very often (several times a week)	169	20	18	23	5	9	244
Too much (daily or almost daily)	133	10	12	30	5	2	192
Total	498	66	76	101	13	27	781
χ^2 Tests							
	Value	p					
Fisher’s exact test		0.013					
N	781						
Monte Carlo simulation							
Nominal							
	Value						
Phi-coefficient	NaN						
Cramer’s V	0.105						

Finally, the association between the frequency of GenAI tool use and participants’ year of study was assessed. Fisher’s exact test (Table 16) was conducted to examine the association between students’ academic year and their frequency of daily generative AI usage ($N = 788$). The analysis revealed no statistically significant association between a student’s year of study and how often they use GenAI tools, ($p = 0.281$). Furthermore, the strength of the relationship between these variables was found to be very weak (Cramer’s $V = 0.085$). These results suggest that the frequency of GenAI tool use was relatively consistent across academic-year categories, from first-year students to students enrolled beyond the nominal duration of their undergraduate program. In the context of this study, the latter category refers to undergraduate students who remain formally enrolled after the standard program duration, a situation that may occur for various reasons, including part-time employment, delayed completion of coursework, examination retakes, interruptions in study, or personal circumstances. Therefore, this category should not be interpreted as indicating a single academic pathway or cause.

Table 16. Fisher’s Exact Test: Does the use of GenAI tools is related to participants academic year?

5. What Academic Year Are You in?							
10. How Often Do You Generally Use Artificial Intelligence (AI) Applications in Your Daily Life?	1st	2nd	3rd	4th	5th	I Have Exceeded the Standard Duration of Study for My Department.	Total
Not at all	1	3	7	6	4	7	28
A little (once a month or less)	11	18	13	19	15	19	95
Moderate (a few times a month)	20	45	43	31	30	53	222
Very often (several times a week)	7	45	50	45	45	56	248
Too much (daily or almost daily)	11	36	29	35	39	45	195
Total	50	147	142	136	133	180	788
χ^2 Tests							
	Value	<i>p</i>					
Fisher’s exact test		0.281					
N	781						
Monte Carlo simulation							
Nominal							
	Value						
Phi-coefficient	NaN						
Cramer’s V	0.0849						

Because several independent association tests were conducted across demographic and educational variables, the resulting *p*-values should be interpreted cautiously. No formal multiple-testing correction, such as Holm or false discovery rate adjustment, was applied in the original analysis. Therefore, subgroup findings are treated as exploratory and non-confirmatory rather than as confirmatory evidence of group differences. In interpreting these results, greater emphasis is placed on effect sizes and practical significance, which were consistently weak or negligible even where uncorrected *p*-values suggested possible associations.

4.4. Patterns of GenAI Tools Usage Among Students

To address the study’s second research question (“How do students utilize GenAI tools in their academic tasks?”), responses to the Yes/No items in Question 11 were analyzed (Q11.A–Q11.A3, Q11.B–Q11.B4, Q11.C–Q11.C3, Q11.D, Q11.E, and Q11.F). The results were informative rather than “enlightening” (Table 17). Out of the 766 students (97.2%) who reported using GenAI tools, the most dominant application was information search, utilized by 85% (*n* = 653) of participants. This finding is consistent with recent studies showing that students commonly use GenAI tools for information seeking, academic support, and study-related assistance [52,53]. Educational and learning purposes also featured prominently, with 59% (*n* = 455) of students using the tools to explain and understand difficult concepts and 48% (*n* = 369) seeking help with academic work, such as paper writing and idea generation. These uses align with prior research describing ChatGPT and related tools as academic assistants that support explanation, writing, brainstorming, and comprehension-oriented learning activities [Y,Z]. Personal assistance and organization also represented a significant use case, adopted by 45% (*n* = 341) of the sample. While programming assistance (36%, *n* = 279) and exam preparation (43%, *n* = 330) were also common, creative applications such as creating or editing videos (7%, *n* = 55) and graphics/presentations (12%, *n* = 89) were notably less frequent. Overall, the data suggest that students primarily

leverage GenAI as a functional support system for information retrieval and academic comprehension rather than primarily as a creative or entertainment-focused tool, a pattern that has also been reported in recent student-focused GenAI studies [52–54]. GenAI tool usage among students is shown in Figure 3 and presented in detail in Table 17.

Table 17. Reported frequencies and percentages of GenAI usage among students.

11. Why Do You Use Artificial Intelligence (AI) Applications?		
	N	%
11.A. Task automation and productivity	255	33%
11.A1. Information search	653	85%
11.A2. Text writing	227	30%
11.A3. Programming (code assistance, algorithm explanation, code debugging)	279	36%
11.B. Education and learning	356	46%
11.B1. Explaining and understanding difficult concepts in simple terms	455	59%
11.B2. Help with academic work (writing papers, generating ideas and inspiration, gathering study material)	369	48%
11.B3. Exam preparation	330	43%
11.B4. Language assistance (conversation practice, translation, grammar)	183	24%
11.C. Creativity	150	20%
11.C1. Creating or editing images	207	27%
11.C2. Creating or editing videos	55	7%
11.C3. Creating graphics, diagrams, presentations	89	12%
11.D. Entertainment (ideas for stories, discussions, entertaining responses)	178	23%
11.E. Personal assistance and organization	341	45%
11.F. Other	0	0%

4.5. Students' Motivations for Using GenAI Tools

In conclusion, this study revealed the students' motivations towards GenAI usage. For this purpose, all the Yes/No Q13 research items' responses were utilized (Q13.1–Q13.11). The results showed (Table 18) that out of the 788 (97.2 %) students who are using GenAI tools, the most dominant motivation towards their usage is to explain and understand difficult concepts (65%, *n* = 499). Information retrieval and study organization also play a central role, with about half of the students using these tools for searching for sources and bibliography (53%, *n* = 408) and for gathering study material (49%, *n* = 374). Additionally, about one third of the participants are motivated by the desire to generate and test ideas or seek inspiration (37%, *n* = 286), for programming/code writing (30%, *n* = 226), and to solve engineering problems (28%, *n* = 213). Only a small fraction of students is motivated to use the GenAI for creativity purposes, including creating/editing images (13%, *n* = 103), graphics/diagrams/presentations (10%, *n* = 75), and videos (4%, *n* = 34). These findings (Figure 4) indicate that students' motivation is overwhelmingly centered on academic comprehension and research efficiency rather than creative content production.

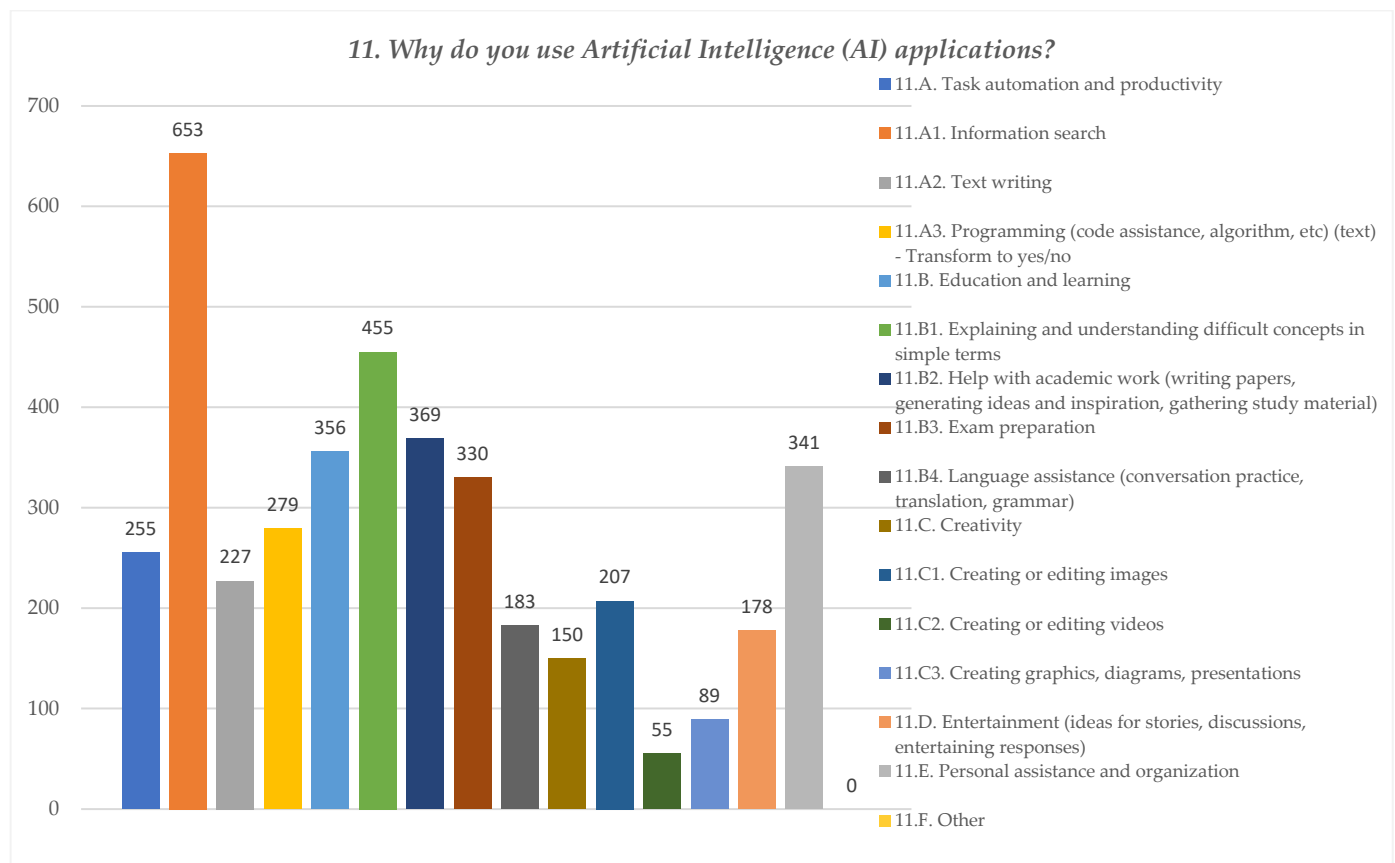


Figure 3. Bar chart showing how students use GenAI tools in academic tasks.

Table 18. Reported frequencies and percentages of students' motivations towards GenAI usage.

13. What Motivates You to Use Artificial Intelligence (AI) Tools?		
	N	%
13.1. To explain and understand difficult concepts	499	65%
13.2 To solve problems, e.g., in mathematics, physics, engineering, etc.	213	28%
13.3. Programming and code writing	226	30%
13.4. Generating and testing ideas, inspiration	286	37%
13.5. Gathering study material	374	49%
13.6. Writing papers	142	19%
13.7. Searching for sources and bibliography	408	53%
13.8. Creating or editing images	103	13%
13.9. Creating or editing videos	34	4%
13.10. Creating graphics, diagrams, presentations	75	10%
13.11. Other	0	0%

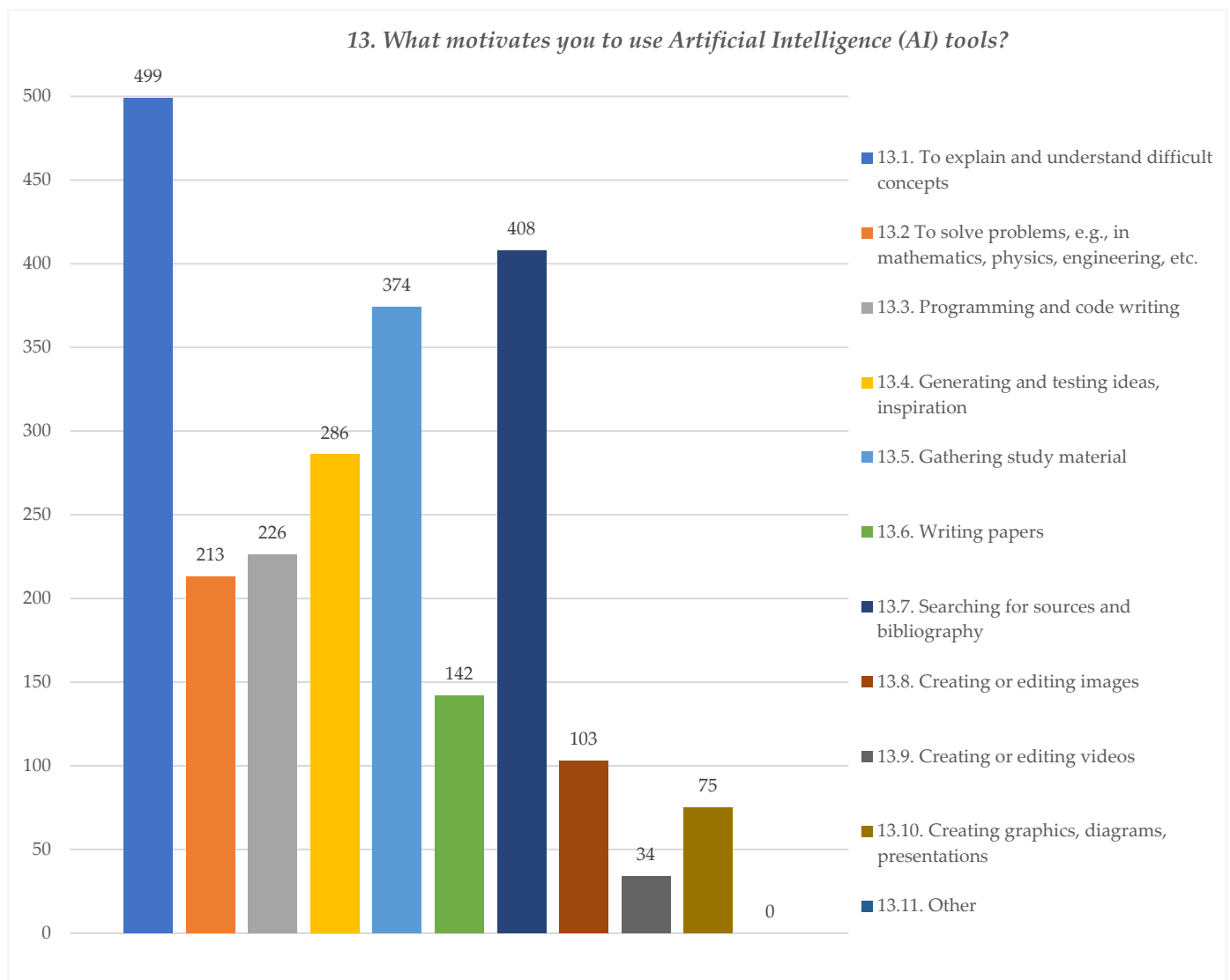


Figure 4. Bar chart showing students' motivations for using GenAI tools in academic tasks.

5. Discussion

The present study provides empirical evidence that GenAI tools have already become deeply embedded in the everyday academic life of undergraduate students at the University of West Attica. The study revealed a remarkably high adoption rate of 97.2%, suggesting that the focus in higher education has shifted from students' utilization of these tools to the ways, frequency, and intentions with which they incorporate them into their learning methods. This discovery aligns with the expanding global body of research indicating the gradual normalization of generative AI tools in university environments [55,56].

To better position the present findings in relation to previous work, Table 19 provides a selective comparison between the current study and representative studies on GenAI use in higher education. The table is not intended as a systematic review, but as a contextual basis for interpreting how the present results align with and differ from prior research.

Table 19. Selective overview of representative studies used to contextualize the present findings on students' GenAI use in higher education.

Study	Context/Sample	Main Focus	Key Positive Findings	Main Concerns/Challenges
Kelly et al. [2]	Students across disciplines	Awareness, experience, and confidence in using GenAI	High awareness of GenAI tools and growing student familiarity across academic fields	Uneven confidence levels and uncertainty regarding appropriate academic use
Chan and Hu [10]	Higher education students	Students' perceptions of generative AI in higher education	Students reported benefits related to brainstorming, writing support, and individualized learning assistance	Ethical use, reliability, privacy, and weakening of independent thinking
Ngo [15]	University students	Perceptions of ChatGPT in education	ChatGPT was perceived as a useful educational aid for explanation, support, and convenience	Inaccuracy, dependency, and superficial engagement with learning
Kharrufa et al. [26]	Software engineering education	Integration of LLMs in team projects	LLMs supported collaboration, productivity, explanation, and technical assistance	Risk of reduced cognitive engagement and overreliance on generated outputs
Almassaad et al. [18]	Higher education students	Utilization, benefits, and challenges of GenAI	Students associated GenAI with efficiency, easier access to information, and academic support	Misuse, inaccuracies, and concerns about authentic learning
Pavlenko and Syzenko [19]	Ukrainian university students	ChatGPT as a learning tool	Students valued ChatGPT for clarification, guidance, and study support	Dependence on AI and questions about the quality of learning
Malmström et al. [21]	University students in Sweden	Use and views of chatbots and AI for learning	AI-supported learning was becoming increasingly normalized among students	Trust, reliability, and broader educational implications of AI-generated content
Chatzopoulos [25]	University education	Use of ChatGPT and other GenAI tools in university settings	Emphasizes the growing role of GenAI in knowledge access, academic support, and study practices	Pedagogical, ethical, and learning-quality implications of widespread adoption

Table 19. Cont.

Study	Context/Sample	Main Focus	Key Positive Findings	Main Concerns/Challenges
Yabaku and Ouhbi [27]	Software engineering students	Perceptions and expectations regarding GenAI tools	Positive expectations regarding programming support, efficiency, and problem-solving	Possible weakening of conceptual understanding if used uncritically
Reihanian et al. [28]	Computer science education literature	Review of GenAI in computer science education	Identified important opportunities for learning support and academic assistance	Accuracy, authenticity, and assessment-related challenges
Mavroudi and Wagstaffe [32]	Systematic review	Digital transformation in university pedagogy	Frames AI adoption as part of a broader pedagogical and institutional transformation	Need to rethink roles, practices, and the relationship between technology and learning

A particularly clear result is the dominance of ChatGPT over all other tools examined. Although students reported use of several systems, including Gemini, DeepSeek, Copilot, Claude, and Perplexity, ChatGPT was by far the most widely used platform. This likely reflects the preference of students for accessible, general-purpose tools that can support a broad range of academic tasks, in contrast to more specialized platforms requiring more specific use cases or greater familiarity.

The findings also show that while GenAI adoption is nearly universal, the intensity of use is more differentiated. A substantial proportion of students reported using these tools several times per week or even daily, whereas another large group used them only occasionally. This suggests that GenAI has already entered students' study routines, but not in a uniform way. For some students it appears to function as a regular academic companion, while for others it remains a supplementary or situational aid.

In terms of usage patterns, students appear to engage with GenAI primarily for pragmatic academic purposes rather than for creative production or entertainment. Information search emerged as the most common use, followed by support for understanding difficult concepts, help with academic work, exam preparation, and personal assistance or organization. Similarly, the strongest reported motivations concerned conceptual understanding, searching for bibliography, and gathering study material. These findings suggest that students mainly perceive GenAI as a functional support mechanism that helps them manage academic demands more efficiently.

The reported use of GenAI tools for source searching and bibliography preparation requires careful interpretation. References are not merely technical outputs, but the evidential basis through which academic arguments are built and connected to existing knowledge. GenAI tools may support early-stage academic work by suggesting keywords, clarifying concepts, or helping students map a topic; however, they cannot replace systematic searching, critical reading, and verification through peer-reviewed literature, academic databases, publisher platforms, library catalogues, and DOI-based checks. This distinction is important because GenAI systems may produce plausible but inaccurate information, including fabricated references. Therefore, universities should integrate GenAI use into explicit AI-literacy and information-literacy training, so that students treat AI outputs as provisional starting points rather than verified scholarly evidence [57–59].

This pattern is especially important because it nuances the common assumption that students primarily use AI as a shortcut for producing ready-made answers. Although concerns about academic integrity, overreliance, and inappropriate use are widely highlighted in the literature, these issues were not directly measured in the present questionnaire. The present findings instead show that students report using GenAI mainly as a tool for information search, clarification, guidance, and study support rather than primarily for creative or entertainment-related purposes. Therefore, the discussion of academic integrity and overreliance should be understood as a literature-based pedagogical implication of widespread academic GenAI use, not as a direct empirical finding about students' concerns [60]. At the same time, this does not eliminate pedagogical concerns. The educational value of GenAI depends heavily on students' ability to critically evaluate, verify, and meaningfully integrate the information it provides. Without such skills, reliance on AI may encourage superficial engagement or uncritical acceptance of inaccurate responses. For this reason, the findings further support the growing importance of AI literacy as part of contemporary higher education, as it enables students to critically evaluate AI-generated content, engage in reflective use of these tools, and address issues related to academic integrity and ethical responsibility.

A particularly important finding concerns the use of GenAI tools for searching sources and bibliography. While this suggests that students increasingly view GenAI as part of their academic workflow, it also raises important questions about source credibility, verification, and knowledge production. General-purpose GenAI platforms can assist students in identifying themes, keywords, search terms, and possible directions for literature exploration; however, they should not be treated as substitutes for academic databases, peer-reviewed sources, or systematic literature-search practices. A major concern is that GenAI tools may generate inaccurate, incomplete, or even fabricated references, while presenting them in a fluent and authoritative manner. This creates a risk that students may confuse plausible-looking output with verified scholarly evidence. Therefore, universities should not simply discourage the use of GenAI for literature-related tasks, but should explicitly teach students how to use such tools responsibly. This includes training students to use GenAI for preliminary orientation, keyword generation, and research-question refinement, while requiring them to verify all sources through credible academic databases, library catalogues, DOI checks, publisher websites, and indexing platforms. In this sense, the challenge is not only technological but pedagogical: higher education institutions need to bridge the gap between AI-assisted information access and academically rigorous knowledge production. Responsible GenAI integration should therefore be accompanied by AI literacy, information literacy, citation-verification practices, and clear institutional guidance on when and how AI-generated suggestions may be used in academic work.

Another notable result is that overall GenAI use was broadly distributed across the student population. No statistically significant associations were found between general use and gender, school of study, or age, while the relationship with professional status, although statistically significant, was practically negligible. This indicates that basic engagement with GenAI is no longer limited to particular student groups, but has become a widespread academic practice.

However, differences did emerge when frequency of use was examined. Gender, professional status, and school of study showed associations with usage frequency in the uncorrected analyses, although all reported effect sizes were small. These results should therefore be interpreted cautiously and as exploratory rather than confirmatory. Nevertheless, they are useful because they suggest that, while basic GenAI adoption is widespread, the intensity of use may vary according to students' academic and social context. Similar patterns have been discussed in previous studies and technology-acceptance frameworks,

which suggest that students' use of AI-based academic support tools may vary according to user characteristics, AI literacy, perceived usefulness, readiness, and educational context [61–63]. In the present study, male students appeared somewhat more likely to use AI more intensively, while employed students also showed slightly more frequent use. These differences may reflect variations in digital confidence, time pressure, disciplinary culture, or the perceived usefulness of GenAI for managing academic and practical demands. However, given the weak effect sizes and the exploratory nature of the pairwise analyses, these patterns should be understood as possible indications of context-sensitive use rather than strong demographic predictors. In this sense, the findings add nuance to the descriptive results: GenAI adoption appears widespread within the surveyed sample, but the degree to which students integrate these tools into their study routines may still differ modestly across groups.

Overall, the findings point to a transitional moment in the surveyed institutional context, where GenAI tools appear to be moving from peripheral technologies toward routine elements of students' reported study practices [64]. Their primary reported value lies in supporting comprehension, information retrieval, and study efficiency. While these patterns resonate with broader debates in higher education, they should be interpreted cautiously because the sample was drawn from a single public university and was strongly weighted toward Engineering-related disciplines. Therefore, the present study does not claim statistical generalizability to higher education as a whole, but provides exploratory evidence that can inform future multi-institutional and more discipline-balanced research [55].

At the same time, the findings of this work point out towards several targeted directions for future research. A useful next step would be to examine similar questions across multiple institutions and with a more balanced disciplinary distribution, so that the extent to which the patterns observed here reflect broader developments in higher education can be assessed more robustly. Comparative studies of this kind would help clarify whether the widespread adoption of GenAI tools is now a general, sector-agnostic characteristic of the contemporary student experience, or whether it still varies in important ways according to institutional culture, field of study, or curriculum structure.

In addition, longitudinal and qualitative approaches would substantially deepen the present picture. Because GenAI tools evolve rapidly, repeated measurements over time could reveal changing patterns of use, trust, dependence, and perceived educational value. Qualitative methods, such as interviews or focus groups, could further illuminate how students interpret the benefits and limits of these tools in practice, how they evaluate their reliability, and how they perceive the boundary between helpful academic support and overdependence on these tools [65].

6. Conclusions

This study examined reported GenAI usage patterns, application contexts, and motivations among undergraduate students at a single public university in Greece. Based on data collected from 788 undergraduate students across multiple schools and disciplines, the findings provide a comprehensive overview of how GenAI tools are currently integrated into students' academic and daily activities.

The results indicate a high level of reported GenAI tool adoption among the surveyed students, with ChatGPT emerging as the most widely used application. Students primarily employ these tools to search for information, support their understanding of academic content, and assist with academic tasks such as writing, exam preparation, and problem-solving. In contrast, creative and entertainment-related uses were reported less frequently. Overall, students reported using GenAI tools mainly for academically oriented

and functional purposes, particularly learning support, information search, academic task assistance, and efficiency enhancement.

At the same time, the broader literature highlights important concerns related to overreliance, inappropriate use, and academic integrity. Since these issues were not directly measured in the present questionnaire, they should not be interpreted as findings of this study. Rather, they provide an important context for interpreting the widespread academic use observed in the sample and reinforce the need for pedagogical guidance, AI literacy, and assessment practices that support responsible GenAI integration.

The study also revealed that GenAI tool usage is widespread across demographic groups, academic schools, and years of study, indicating that these technologies have become an integral part of the contemporary student experience rather than a niche or discipline-specific phenomenon. Differences observed in usage frequency across certain groups were generally small, suggesting a broadly shared pattern of adoption and use.

Overall, this research contributes empirical evidence to the growing body of literature on Generative AI in higher education by providing a large-scale, data-driven perspective on students' reported real-world practices. At the same time, the findings should be interpreted in light of the study's methodological limitations. The sample was drawn from a single public university and was strongly weighted toward Engineering-related disciplines, while participation was voluntary and based on self-reported data. In addition, the questionnaire was purpose-built for exploratory mapping rather than full psychometric validation, and some analyses relied on simplified use/non-use indicators and exploratory subgroup comparisons. These limitations do not undermine the value of the findings, but they define the scope within which they should be interpreted. Future research could build on this work in several ways. These include examining longitudinal trends, using multi-institutional and more discipline-balanced samples, retaining the full ordinal structure of survey responses, applying multivariable or ordinal modelling approaches, and incorporating qualitative perspectives from both students and educators.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Abbreviations

The following abbreviations are used in this manuscript:

LLM	Large Language Model
GenAI	Generative Artificial Intelligence
AI	Artificial Intelligence

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