

Students' Awareness, Perceptions, and Use of Generative AI Tools in Higher Education

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Abstract: *The integration of digital technologies, content and processes is reshaping all sectors of education, from curriculum reform to teacher assessment and development. Among these technologies, generative artificial intelligence (AI) presents significant opportunities to improve the learning experience, especially in secondary and higher education, but it also raises questions about accuracy, academic integrity, privacy, and institutional guidance. This study examines how students perceive and use AI as a learning tool and how AI applications are integrated into academic processes and learning activities. A structured questionnaire was administered in two phases to students from five universities in four countries; the analysis dataset contained 227 consenting respondents. We report item-specific denominators, confidence intervals for key proportions, nonparametric comparisons for ordinal outcomes, effect sizes, Holm correction for multiple comparisons, and sensitivity analyses adjusted for recruitment phase and institution. Most respondents reported prior AI use, frequent use, and positive learning perceptions, while almost all users had encountered incor-*

rect output. Only a minority knew that institutional AI-use guidelines existed, although most supported formal policies and explicit ethical-use instruction. Gender differences were generally small after multiplicity correction; women more often reported grammar/writing tools and problem-solving use. The findings support clearer institutional guidance, AI-literacy training, verification practices, and responsible-use policies rather than simple promotion or prohibition of AI tools.

Index Terms: *AI, ChatGPT, Generative AI, Higher Education, Teaching and Learning, Student Engagement*

1. INTRODUCTION

OVER the past decades, the rapid and unprecedented growth of technologies applied in education and various other sectors has been clearly evident [20, 22, 43]. Digital technologies, digital content, and related processes exert a significant influence across all sectors of education—including primary and secondary schooling, higher education, and informal learning environments—shaping the entire educational value chain, from curriculum reform and instructional practices to assessment and teacher professional development, while actively engaging educators, learners, and institutional leaders.

Applications based on Artificial Intelligence have a huge contribution in everybody's daily life. In addition, AI (based on a model) offers a wide range of potential benefits for students and teachers. AI in education poses challenges, demanding research and practical application [12]. Effective data use, ethics, and AI advancement require skill development for teachers, administrators, and students.

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Currently one of the most popular and widely used tools, ChatGPT, can assist students in: developing communication skills in a foreign language [13, 18]; in programming [39]; creating content, answering questions, explaining concepts, and giving suggestions [19, 49]; assist in conducting literature reviews [26]. Notably, more than a half of college students have used AI on assignments or exams [35].

Researchers are dedicated to developing educational visualization tools and studying their impact on the teaching process [27, 41, 42]. Since the education sector has benefited enormously through the integration of tools and platforms driven by digital technology, many authors analyze modern AI tools available to learners and educators [8, 9, 14, 18, 29, 31, 34, 38]. Further, the European Education Area (EEA) initiative [1] aims to strengthen national education systems by promoting resilience, inclusiveness, and the integration of digital learning and pedagogies, while supporting policy-makers in designing, implementing, and evaluating initiatives related to digital education.

The primary objective of this study is to examine how AI can impact on teaching and learning in secondary and higher education. This study, therefore, aimed to examine students' attitudes toward AI through a cross-sectional analysis. Our research questions focus on students' access to AI tools, their perception of AI in education, the perceived usefulness of AI tools for learning, and potential gender-related differences in these perceptions.

We investigate the following research questions:

- RQ1** What access, familiarity, use frequency, tools, and academic-task purposes do students report?
- RQ2** How do students evaluate AI's learning effectiveness and support for independent learning, and what do they report about trust and incorrect output?
- RQ3** What relationships connect AI-use intensity and purpose, complete-task generation, integrity attitudes, treatment preferences, detection awareness, and institutional governance?

- RQ4** Which gender differences in AI access, use, learning perceptions, and responsible-use outcomes are supported after effect-size estimation, multiplicity correction, and sensitivity adjustment for recruitment phase and institution?

This paper is a significant extension and improvement of our preliminary work [44], in the following ways:

- We included students from Serbia and Slovenia in the second round of the study;
- We expanded the Results section;
- We added a Discussion section and Supplementary Material section.

The study that was inspired by research conducted by [7].

The main contributions of the article are as follows:

- providing an international empirical analysis of students' awareness, perception and use of AI tools in higher education, based on data collected from universities in four European countries;
- identifying patterns in how students integrate generative AI tools into their learning activities, including programming, problem-solving and academic writing;
- exploring gender differences in students' perceptions and use of AI tools in educational contexts;
- highlighting implications for educators and institutions regarding the responsible and effective integration of AI tools into teaching and learning.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology. Section 4 presents the results and answers to research questions. Section 5 discusses the findings: general awareness and usage of AI tools; ethics, policy, and responsible use; and gender-related patterns. Finally, Section 6 concludes the paper and outlines directions for future research.

2. RELATED WORK

This paper examines the use of AI tools in higher education and analyzes their potential impact on teaching and learning. The literature shows that researchers have extensively examined the transformative role of AI in teaching and learning.

As educational institutions increasingly rely on digital platforms and online learning systems, students and teachers increasingly interact through various online communication tools and social networks [15]. In such environments, similar security and privacy challenges arise and must be addressed to safeguard sensitive educational data.

The EU increasingly emphasizes digital transformation and the use of AI in education, as reflected in the AI Act and the Coordinated Plan on AI. One of the European Commission framework projects is SELFIE [3] (Self-reflection on Effective Learning by Fostering the use of Innovative Educational technologies). Digital learning technologies, in the context of DigCompOrg [2], constitute a key enabler for educational organizations, which can support their efforts to achieve their particular mission and vision for quality education.

Recent research has increasingly focused on the use of generative AI tools, particularly ChatGPT, in higher education. Several review studies summarize the opportunities and challenges associated with the use of ChatGPT in educational contexts [5]. Early reviews of ChatGPT in education highlight both the opportunities and the challenges associated with its use in educational contexts [21].

Qualitative research [23] provides an overview of the effectiveness of using ChatGPT as a virtual assistant. It helps improve student productivity in higher education by providing useful information and resources, supporting language development, facilitating collaboration, improving time efficiency, and offering motivation and support. Baidoo-Anu and Ansah discuss in [7] the benefits of ChatGPT and related generative AI technologies for advancing teaching and learning. They also identify several potential drawbacks, such as generating incorrect information, biases in training

data that may reinforce existing biases, and privacy concerns. In addition, the study [33] emphasizes the potential of ChatGPT as a tool for enhancing English as a Foreign Language students' English language proficiency.

Some studies report less positive outcomes. For example, [32] found that ChatGPT did not improve performance across several disciplines, while Wu [50] warns that rapid automated answers may create an illusion of understanding. In addition, Haman [26] shows that ChatGPT may generate inaccurate or even non-existent references when used for literature searches, raising concerns about its reliability in academic research.

Currently, there are not many studies that observe using ChatGPT for teaching and learning in data science education, so paper [51] incorporates ChatGPT into a data science course and collects valuable insights from students, as well as sharing feedback from the instructor. The findings highlight the uniqueness of data science education while revealing new opportunities and challenges in integrating ChatGPT into the curriculum. Bin-Nashwan et al. [10] suggest to educators, policymakers, and technology developers that they have to work collaboratively to establish frameworks that promote responsible and ethical use of ChatGPT in education.

Focus on ChatGPT is also given through analysis of the significance and utilization of artificial intelligence in learning systems in higher STEM education [28]. In addition, the study [46] found that students viewed ChatGPT as an innovative set of AI tools that can be used in classroom settings, including programming and computer languages, promoting sustainable adoption of AI in education. In addition, the study [37] showed that the integration of GPT and innovative learning methods significantly improved academic performance and motivation.

Chen et al. [17] systematically reviews AI applications in education, including personalized learning, intelligent tutoring systems, and automated assessment. It also addresses technical, ethical, and pedagogical challenges, emphasizing the need for balanced integration of AI with human-centered teaching approaches.

Another overview of AI's integration into educational settings is given in [36]. Ng et al. discuss various applications such as intelligent tutoring systems, personalized learning platforms, and automated assessment tools, highlighting their potential to improve educational outcomes. Likewise, Lameris et al. [30] discuss the evolution of AI applications: from early computer-based tools to advanced systems such as intelligent tutoring, adaptive learning platforms, and humanoid robots, highlighting their impact on administrative efficiency, personalized instruction, and improved learning outcomes. Together, these studies demonstrate the growing role of AI technologies in shaping modern educational environments.

In addition, the review [31] categorizes AI applications in education into proactive (e.g. admissions, course scheduling, content generation) and reactive (e.g. knowledge delivery, performance assessment, outcome prediction) phases. It examines research trends over two decades, highlighting how AI methods support various educational stakeholders and discussing the evolution of solution approaches in the field. Besides that, Guo et al. in [25] examine teachers' acceptance of AI (TAAI) in educational settings. The instrument assesses five dimensions: perceived usefulness, perceived ease of use, behavioral intention, self-efficacy, and anxiety.

At the same time, the use of generative AI (GenAI) in teachers' daily practice offers substantial potential to enhance teaching, but also introduces new risks and responsibilities [11, 16, 40, 45]. The study [24] explores how AI simulations acting as both virtual students and mentors help preservice mathematics teachers develop teaching skills and professional identity through interactive practice and feedback.

Unlike the other reviews, Tan et al. noticed and highlighted a gap in research [48] addressing the development needs of teachers as they integrate AI technologies into their teaching practices, emphasizing the need for future research to further explore the potential of AI in teacher professional development and to investigate how AI technologies can be applied in education from both the perspectives of student learning and teacher instruction.

Motivated by these findings, our study de-

velops a questionnaire to examine students' awareness, perception, and usage of AI tools in teaching and learning, including ethical considerations.

3. METHODOLOGY

The research data in this study was collected through the primary data collection – a questionnaire [47]. Data were collected online using Google Forms [4] from students in two phases: first during the beginning of the summer semester of 2024/2025 (April 2025), and second during the end of the winter semester of 2025/2026 between January and February 2026. The study took a random sample of students with similar backgrounds: computer science, information technologies, AI, cybersecurity, mathematics and applied mathematics.

Data were therefore collected from student classes that were available to the researchers at the time from universities in Poland, Slovakia, Slovenia and Serbia. The questionnaire was written in English. Before taking part in the study, participants were informed of its general purpose and provided their informed consent.

The questionnaire includes closed-ended questions with binary response options (yes/no), Likert scales, check-boxes for multiple answers, and open questions with the opportunity for short written answers. This questionnaire design was intended to give a mix of both qualitative and quantitative data.

The AI tools questions used the phrase "AI tools" or "AI Assistants (Chatbots)" (e.g. "What AI tools have you used in an educational context?"), rather than to just emphasize "ChatGPT" since students use different AI tools.

The first section of the questionnaire gathered students' general demographic information such as age, gender, and educational status. The second section assessed perceived general perception, awareness, and usage of AI in students' field, while the third section measured attitude toward usage of AI tools. The fourth section observe the level of satisfaction while using them in teaching and learning, ethics, and confidence. Final part examines the consideration of the AI use for students who still have

not used AI.

The data corpus was analyzed using survey content analysis to identify themes and patterns, providing insights into the potential role of AI tools in education, and, descriptive statistics for the data collected (reported based on counts and ratios) is coded manually from Google spreadsheets and prominent themes identified. In addition, comparative analysis between male and female students was performed in order to examine potential gender-related differences in the perception and use of AI tools.

3.1 Participants

The study results presented in the article are obtained from a data sample of a total of 228 students from five universities: Cardinal Stefan Wyszyński University in Warsaw, Poland (42 students), Technical University of Košice, Slovakia (76 students), Matej Bel University, Banská Bystrica, Slovakia (11 students), University of Maribor, Faculty of Organizational Sciences, Kranj (10 students), University of Novi Sad (Faculty of Sciences, Faculty of Technical Sciences), Serbia (89 students).

In the first phase participated 84 students from two universities: Cardinal Stefan Wyszyński University in Warsaw, Poland (36 students), and Technical University of Košice, Slovakia (48 students). While, in the second phase participated 144 students from five universities: Cardinal Stefan Wyszyński University in Warsaw, Poland (6 students), Technical University of Košice, Slovakia (28 students), Matej Bel University, Banská Bystrica, Slovakia (11 students), University of Maribor, Faculty of Organizational Sciences, Kranj (10 students), University of Novi Sad (Faculty of Sciences, Faculty of Technical Sciences), Serbia (89 students). Detailed data related to the sample for each university is given in the Table 1; a visual summary of the unequal institutional composition is provided in Supplementary Fig. S2.

The highest level of education completed by 77.19% of the students is high school (pre-university entry, usually taken at age 18), 18.86% have bachelor's degree, and 3.95% have master's degree.

Table 1: Detailed data related to the sample for each university

Institution	<i>n</i>	%
University of Novi Sad, Serbia	88	38.8
Technical University of Košice, Slovakia	76	33.5
Cardinal Stefan Wyszyński University in Warsaw, Poland	42	18.5
Matej Bel University, Banská Bystrica, Slovakia	11	4.8
University of Maribor, Faculty of Organizational Sciences, Slovenia	10	4.4

70 students considered themselves female (30.70%), while 154 students identified as male (67.54%). Two students (0.88%) identified as non-binary/third gender, and two students (0.88%) preferred not to disclose their gender. There was some concern about the gender ratio; however, it is common in these types of the study. Table 2 presents the description of the participants by gender in this study (total and by Universities).

Table 2: Distribution of students by gender

Gender	<i>n</i>	%
Male	154	67.8
Female	69	30.4
Non-binary/third gender	2	0.9
Prefer not to say	2	0.9

Table 3: Distribution of students by age

Age range	<i>n</i>	%
18–20	99	43.6
21–23	93	41.0
24–26	15	6.6
27–30	13	5.7
31 or older	6	2.6
Prefer not to answer	1	0.4

In the present sample, the average age was 21.74, while the median age was 20 years (ranging from 18 to 46 years, $SD = 3.76$). Two students preferred not to disclose their age. Table 3 presents the distribution of the students by age range in this study.

25 students are major in mathematics, 5 in applied mathematics, 2 in teaching CS and mathematics, 55 in computer science, 114 in information technologies/informatics, 5 in cy-

bersecurity, 3 in AI, 11 in applied informatics, and 8 in management of information systems.

The results related to RQ1 indicate that 68.86% of all students consider that they have access to AI tools in their educational environment, 20.61% are not sure, while 10.53% consider that they do not have access. Correspondingly, similar ratio is between genders as shown in Table 4.

Table 4: Frequency of access to AI tools in your educational environment (by gender)

Response	Male	Female	All respondents
Yes	107	47	157
No	17	6	23
Not sure	31	16	47

4. RESULTS

The survey questionnaire was crafted to gather in-depth insights from participants, including questions that explored the perceived benefits of using AI tools in learning and any challenges faced during their use.

4.1 General Awareness and Usage of AI tools

The survey was designed to explore the attitudes of students to the use of AI tools in their field and in their education. The revised analysis uses the respondent-level data consistently and reports denominators for each item. Access to AI tools in the educational environment was reported by 157 of 227 students (69.2%, 95% CI 62.9%–74.8%); 47 students were unsure and 23 reported no access. Moderate or extreme familiarity with AI tools was reported by 161 of 227 students (70.9%). Prior use of AI tools was reported by 214 of 227 students (94.3%, 95% CI 90.4%–96.6%).

Among the 214 AI users, 173 students (80.8%, 95% CI 75.0%–85.6%) used AI at least two to four times per week. ChatGPT was the most frequently reported assistant (197/214, 92.1%), followed by Gemini (97/214, 45.3%), Microsoft Copilot (67/214, 31.3%), Claude (48/214, 22.4%), and DeepSeek (20/214, 9.3%). Multiple tools could be selected. The leading task selections were solving problems

(169/214, 79.0%), programming (150/214, 70.1%), teaching-related support (94/214, 43.9%), writing homework or tasks (63/214, 29.4%), and writing essays (51/214, 23.8%). These results confirm that the use of AI tools is not limited to one product or one task type.

A graphical version of the key AI-use, learning, integrity, and governance outcomes is provided in Supplementary Fig. S1.

To measure students' attitudes toward the effectiveness of AI in enhancing student learning outcomes, responses were obtained using a 7-point Likert scale. Among AI users, 168 of 214 respondents (78.5%) rated AI as at least slightly effective for learning. However, positive evaluations were accompanied by caution: 210 of 214 users (98.1%) reported encountering incorrect AI output, while 191 of 214 (89.3%) nevertheless reported at least some trust in AI tools. This combination suggests conditional reliance rather than uncritical confidence.

4.2 Ethics, Policy, and Responsible Use

The ethics questions show a clear governance gap. Only 53 of 214 AI users (24.8%) knew that their institution had AI-use guidelines, whereas 131 of 214 (61.2%) supported formal policies and 139 of 214 (65.0%) supported explicit teaching about ethical AI use. Nearly half of AI users (100/214, 46.7%) reported using AI to generate complete homework tasks, while 124 of 214 (57.9%) agreed or strongly agreed that AI-assisted dishonesty threatens educational integrity.

Students who reported complete-task generation gave lower integrity-threat ratings than students who did not in the unadjusted comparison, but this association was not retained in the adjusted dichotomized sensitivity model. Complete-task generation increased across the ordered use-frequency scale and was most common among daily users. In the adjusted model, programming and teaching purposes remained associated with complete-task generation. The association between guideline visibility and policy demand was also important: students who knew that guidelines existed more often supported formal policies than other respondents. The most frequent treatment preferences were

Table 5: Key learning and responsible-use outcomes

Outcome	<i>n/N</i>	%	95% CI
Prior AI use	214/227	94.3	90.4–96.6
Use at least 2–4 times weekly	173/214	80.8	75.0–85.6
At least slightly effective for learning	168/214	78.5	72.5–83.5
Somewhat/mostly trusts AI	191/214	89.3	84.4–92.7
Encountered incorrect output	210/214	98.1	95.3–99.3
Generated complete homework	100/214	46.7	40.2–53.4
Integrity threat: agree/strongly agree	124/214	57.9	51.2–64.4
Teach ethical use: yes	139/214	65.0	58.3–71.0
Institution has guidelines: yes	53/214	24.8	19.5–31.0
Formal policies should exist: yes	131/214	61.2	54.5–67.5

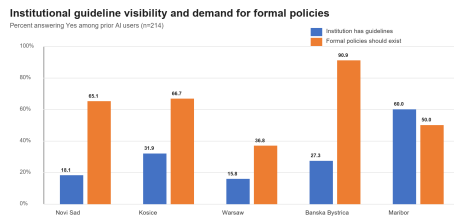


Figure 1: Institutional guideline visibility and demand for formal AI-use policies among prior AI users.

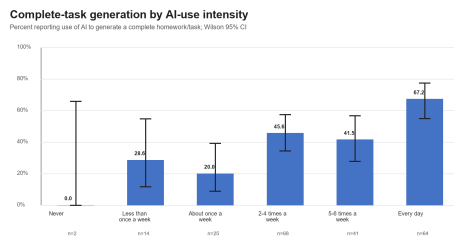


Figure 2: Complete-task generation by AI-use frequency, with Wilson 95% confidence intervals.

adaptation rather than punishment and recognizing a shift in learning and assessment. Detection awareness was not reliably associated with lower complete-task generation after within-family correction.

Figure 1 summarizes the most policy-relevant institutional result.

Figures 2 and 3 show the two ethical-behaviour results that are most directly actionable for teaching and policy design. Additional ethics analyses are retained in the supplementary material: the integrity-threat distribution

by complete-task behaviour is shown in Supplementary Fig. S6, detection awareness and behaviour in Supplementary Fig. S7, and adjusted ethics associations in Supplementary Fig. S8.

4.3 Gender-related Patterns

The analysis aimed at evaluating RQ4 shows that some gender differences can be observed, but they are more limited than the descriptive figures alone suggest. Male and female respondents had similar access, use frequency, perceived learning effectiveness, and views of learner independence. None of the six primary ordinal comparisons remained significant after Holm correction. Women more often selected grammar and writing improvement tools and problem solving as a task, and these differences survived correction within their multiple-response families. Programming was more common among men before correction but not after correction. An adjusted sensitivity model suggested lower odds of moderate-or-higher familiarity among women, but this result depends on dichotomization and should be treated as exploratory. The detailed gender-stratified tool and task selections are shown in Supplementary Fig. S3, adjusted gender sensitivity models in Supplementary Fig. S4, and the primary ordinal gender comparisons in Supplementary Fig. S5. These figures are useful for transparency but are kept outside the main manuscript to preserve space and avoid overemphasizing exploratory subgroup findings.

Preferred responses to AI-assisted academic dishonesty

Selection prevalence by complete-task behavior; multiple responses permitted

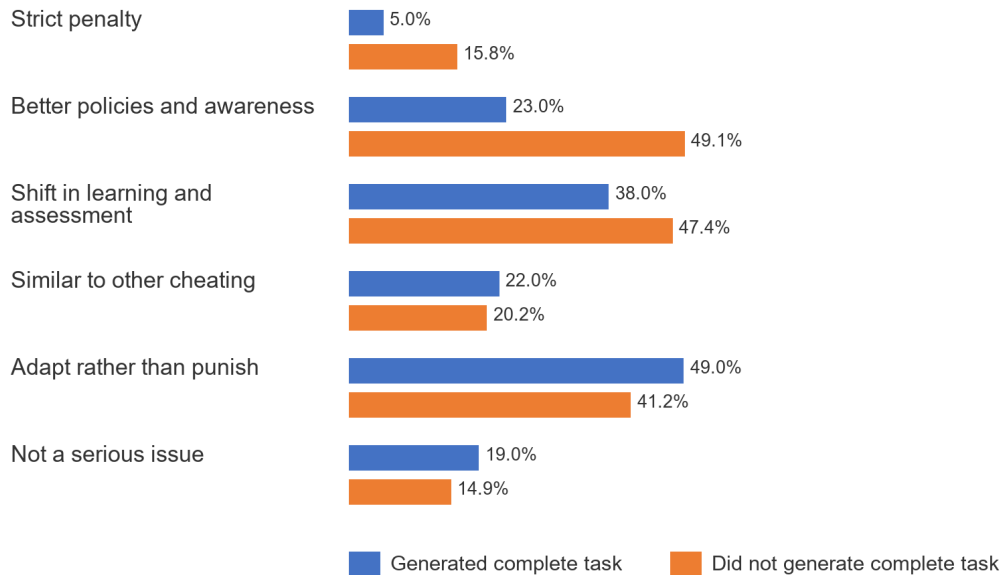


Figure 3: Preferred treatment of AI-assisted academic dishonesty; multiple selections were permitted.

5. DISCUSSION

The results reached in this study bring the answers to the research questions presented in the Introduction. Findings regarding RQ1 show that most students in this technology-focused convenience sample have used AI tools and use them frequently for problem solving, programming, teaching-related support, homework or tasks, and writing. Regarding RQ2, students generally perceive AI as useful for learning, but this positive perception is accompanied by widespread experience of incorrect output. The results related to RQ3 show that ethical and institutional questions are not peripheral: many students report complete-task generation, most support ethical-use instruction, and many do not know whether institutional guidelines exist. RQ4 shows that gender-related differences are present in selected tool and task choices, but broad claims about gender differences are not supported after correction for multiple comparisons.

The use of technology and the Internet is

continuously transforming education, leading to the introduction of new methods and virtual learning environments in teaching and learning processes. However, the extent to which these innovations are effectively implemented largely depends on teachers' expertise, students' AI literacy, institutional policy visibility, and the design of assessment. Universities and faculties can recommend innovative approaches and provide support through seminars, professional development programs, and the provision of appropriate technological infrastructure.

The findings suggest that universities should not treat AI only as a technical tool. They should define acceptable assistance, disclosure and citation expectations, responsibility for errors, use in examinations, handling of confidential data, and consequences for noncompliance. Training should require students to verify claims and code, compare outputs with authoritative sources, document substantial AI assistance, and avoid entering personal, assessment, research, or proprietary data into tools without authorization. Since detection awareness was

not associated with lower complete-task generation, prevention should rely more on clear rules, assessment design, and responsible-use education than on detection alone.

The study has limitations. The sample was recruited by convenience from five universities and is not representative of national student populations. Institution, country, recruitment phase, field of study, and gender composition are partly confounded. The questionnaire was investigator-developed and was not psychometrically validated; therefore, item groups should not be interpreted as latent constructs. The results are self-reported and cross-sectional, so they cannot establish causal effects or actual learning outcomes. Future studies should use preregistered hypotheses, balanced sampling, validated AI-literacy and adoption measures, qualitative coding of open responses, and longitudinal or intervention designs.

6. CONCLUSION

The results of our study present empirical evidence regarding the perception and use of AI tools by students in higher education. The findings show that AI tools are widely used and generally considered beneficial for supporting educational activities, programming, problem solving, and academic writing. At the same time, the results show that frequent use coexists with incorrect AI output, partial trust, complete-task generation, and limited awareness of institutional guidelines.

The statistical and ethics analyses suggest that universities should combine access to AI tools with explicit instruction in verification, disclosure, privacy, academic integrity, and acceptable assistance. Gender-related findings should be interpreted cautiously: selected tool and task differences were observed, but most primary comparisons were small and did not remain significant after multiplicity correction. These findings underline the importance of clear institutional policies and AI literacy rather than broad claims about student groups.

In this research, we have identified some of the challenges that higher education institutions and students may face as a result of the expansion and integration of new technologies

into teaching and the pedagogical process. The findings of this study can serve for our future research, especially in areas that require analytical reasoning and structured thinking, such as theoretical computer science and formal methods. Future studies should use stronger sampling, validated measures, and longitudinal or intervention designs to evaluate whether AI-literacy and policy training improve responsible use and learning outcomes.

ETHICS AND DATA AVAILABILITY

Participation was voluntary. Respondents received information about the study purpose and provided consent before accessing the questionnaire. Four submissions that declined consent contained no study responses and were excluded. The study used an anonymous online questionnaire, collected no directly identifying personal data, involved adult university students, and presented no more than minimal risk to participants. According to the applicable institutional and national regulations for anonymous educational survey research, formal ethics committee approval was not required. The de-identified survey data in Excel format, analysis code, and aggregate Excel and PNG outputs are available from the corresponding author upon reasonable request.

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SUPPLEMENTARY MATERIAL

DATA RECONCILIATION AND ANALYSIS POPULATION

The combined worksheet contained 231 submissions. Four records declined consent and contained no study responses, leaving 227 participants. Respondent-level data contain 154 men, 69 women, two non-binary/third-gender respondents, and two respondents who preferred not to state gender. Phase 1 contains 84 records and phase 2 contains 143, including one March 2026 timestamp. Institution counts are Novi Sad 88, Košice 76, Warsaw 42, Banská Bystrica 11, and Maribor 10. All descriptive results retain the four non-binary or undisclosed-gender records. Male–female inferential comparisons exclude them because the individual cells are too small for stable estimation. Multiple-response percentages use the complete item denominator and can sum to more than 100%. Missing responses are not imputed.

QUESTIONNAIRE AND CODEBOOK

Table S1 lists the questionnaire items relevant to this study. The wording follows the supplied workbook headers, while the first column uses short semantic labels rather than spreadsheet column letters. Coding questions and open-text items are retained for reproducibility but were not used for unsupported qualitative inference in the revised manuscript.

Table S1: Questionnaire items, response formats, and analysis coding

Item	Item wording	Response format and analysis use
Consent	Consent to participate	Yes or No; No ended the survey.
Age	What is your age?	Open numeric; one nonnumeric refusal treated as missing.
Gender	What is your gender?	Male; Female; Non-binary/third gender; Prefer not to say.
Education level	Highest education completed	Elementary school; High school; Bachelor's; Master's.
Institution type	Type of institution	Categories as presented in the form.
Institution name	Name of institution	Open text; standardized into five institutions.
Field of study	Field of study or subject area	Open text; used descriptively.
Country	Country of study	Open text; used descriptively.
AI access	Access to AI tools in the educational environment	No; Not sure; Yes; ordered 0–2.
Field role of AI	Perceived role of AI in the respondent's field	Open text; excluded from formal qualitative inference.
AI familiarity	Familiarity with artificial intelligence	Five ordered categories; stored 1–5.
Prior AI use	Prior use of AI tools in work or daily life	Yes or No; determines user/non-user branch.
Tool categories used	Types of AI tools used	Multiple response: assistants; writing; search; video; presentations; image; notetakers; music; other.
AI-use frequency	Frequency of AI-tool use	Never; less than weekly; once weekly; 2–4 times weekly; 5–6 times weekly; daily; ordered 0–5.
Assistant brands	AI assistants/chatbots used	Multiple response including ChatGPT, Gemini, Copilot, Claude, DeepSeek, and other.
Assistant choice reasons	Reasons for using AI assistants	Multiple response: free; popular; recommended; other.
Willingness to pay	Willingness to pay for AI assistants	No; Maybe; Yes.
Teaching/learning use	Use of AI to support teaching or learning	Yes or No; four AI-user records missing.
AI-use purpose	Primary tasks for which AI is used	Multiple response: problem solving; programming; teaching; homework/tasks; essays; other.
Adoption motivation	Motivation for adopting AI in learning	Open text; excluded from formal qualitative inference.
Educational AI tools	AI tools used in an educational context	Multiple response using the categories in tool categories used.
Learning effectiveness	Effectiveness of AI in enhancing learning outcomes	Seven ordered categories from absolutely ineffective to absolutely effective; stored 1–7.
Independent learning	Whether AI helps students become independent learners	No; Maybe; Yes; ordered 0–2.
Complete-task generation	Use of AI to generate complete homework tasks	Yes or No; primary behaviour outcome for the ethics analyses.

Table S1 continued

Item	Item wording	Response format and analysis use
Integrity-threat attitude	AI-assisted dishonesty as a serious integrity threat	Five-point agreement item; stored 1–5.
Ethical-use teaching	Whether students should be taught ethical AI use	No; Maybe; Yes; ordered 0–2.
Treatment preferences	How AI-assisted dishonesty should be treated	Multiple response; descriptive.
Plagiarism-detection awareness	Awareness of plagiarism-detection software	Yes or No.
AI-detection awareness	Awareness of AI-detection tools	Yes or No.
Institutional guideline visibility	Institution has AI-use guidelines	No; I do not know; Yes.
Formal policy demand	Formal AI policies should exist	No; I do not know; Yes; ordered 0–2 for exploratory comparison.
Replacement expectation	Whether AI will replace teaching tasks or roles	No; I do not know; Yes.
Trust in AI output	Trust in AI-generated output	Five ordered categories from none to full trust; stored 1–5.
Trusted-output contexts	Contexts in which AI output is trusted	Multiple response: source verification; basic tasks; understood process; tool-dependent; human oversight; other.
Incorrect AI answers	Encountered incorrect AI answers	Yes or No.
Correction attempts	Asked AI to correct an incorrect answer	Yes or No.
Coding use	Use of AI for coding	Intended Yes/No; one observed Maybe response retained descriptively.
Coding-use frequency	Frequency of AI use for coding/software engineering	Rarely; Sometimes; Frequently; Always; some nonstandard form-version entries.
Software-engineering tasks	Software-engineering tasks using AI	Multiple response: requirements; design; coding; debugging; testing; documentation; other.
Coding prompt style	Best description of coding prompt use	Basic or proficient prompt-use description.
Debugging support	How AI help is requested for debugging	Multiple response: paste errors; ask for explanations; step-by-step prompts; other.
Advanced prompting	Advanced prompting used	Multiple response: none; few-shot; chain-of-thought; role-based; constraints.
AI work checking	Whether AI work is checked	Always or sometimes in the implemented dataset.
AI-use struggles	Biggest struggle with AI	Multiple response and other text: mistakes; overreliance; ethics; other.
Help/failure example	Example where AI helped or failed	Open text.
Desired AI skills	AI skills the respondent wants to learn	Open text.
Prompt-pattern knowledge	Knowledge of prompt patterns	Yes or No.
Non-user consideration	Intention to consider AI	No; Maybe; Yes; non-user branch only.
Non-user education intent	Intention to use AI in education	No; Maybe; Yes; non-user branch only.

COMPLETE GENDER COMPARISONS

Multiple-response educational tools

Table S2: Educational tool selections by gender among AI users

Option	Female <i>n</i> / <i>N</i>	Male <i>n</i> / <i>N</i>	OR	95% CI	Holm <i>p</i>
AI assistants/chatbots	57/65	140/146	0.31	0.10–0.92	0.256
Grammar/writing improvement	33/65	44/146	2.39	1.31–4.36	0.042
Search engines	22/65	64/146	0.66	0.36–1.21	1.000
Video generation/editing	2/65	4/146	1.13	0.20–6.31	1.000
Presentations	10/65	17/146	1.38	0.59–3.20	1.000
Image generation	9/65	20/146	1.01	0.43–2.36	1.000
Notetakers/meeting assistants	4/65	14/146	0.62	0.20–1.96	1.000
Music generation	0/65	1/146	0.00	0.03–18.42	1.000

Multiple-response task purposes

Table S3: Task-purpose selections by gender among AI users

Option	Female <i>n/N</i>	Male <i>n/N</i>	OR	95% CI	Holm <i>p</i>
Solving problems	59/65	108/146	3.46	1.38–8.66	0.028
Programming	39/65	109/146	0.51	0.27–0.95	0.142
Teaching	29/65	65/146	1.00	0.56–1.81	1.000
Writing homework/tasks	17/65	45/146	0.79	0.41–1.53	1.000
Writing essays	13/65	37/146	0.74	0.36–1.50	1.000

Assistant brands

Table S4: Assistant-brand selections by gender among AI users

Option	Female <i>n/N</i>	Male <i>n/N</i>	OR	95% CI	Holm <i>p</i>
ChatGPT	62/65	132/146	2.19	0.61–7.91	1.000
Gemini	31/65	66/146	1.11	0.62–1.99	1.000
Microsoft Copilot	23/65	44/146	1.27	0.68–2.36	1.000
Claude	12/65	36/146	0.69	0.33–1.44	1.000
DeepSeek	6/65	13/146	1.04	0.38–2.87	1.000

ADJUSTED SENSITIVITY MODELS

Binary outcomes were analyzed with logistic regression adjusted for recruitment phase and institution. These are sensitivity analyses, not replacements for the ordinal primary analyses. Holm correction was applied across the seven models.

Table S5: Phase- and institution-adjusted gender sensitivity models

Outcome	<i>n</i>	Events	Adjusted OR	95% CI	Holm <i>p</i>
Access: yes	223	154	0.92	0.49–1.73	1.000
Familiarity: moderate or higher	223	158	0.34	0.18–0.66	0.009
Use 5–6 times weekly or daily	211	104	1.05	0.58–1.91	1.000
Effective or absolutely effective	211	120	0.79	0.43–1.45	1.000
Independent learner: yes	211	95	1.14	0.62–2.12	1.000
Integrity threat: agree/strongly agree	211	122	0.46	0.25–0.86	0.089
Generated complete homework: yes	211	99	0.76	0.41–1.42	1.000

ETHICS AND GOVERNANCE ANALYSES

Analyses in this section include the 214 prior AI users who received the ethics and governance items listed in Table S1. Site comparisons retain the three response categories for institutional guideline visibility and formal policy demand and use 10,000-permutation chi-square tests. Holm correction was applied across the two site outcomes and separately within the purpose, treatment-preference, and detection-awareness families. Odds ratios compare the first named group with its reference group. Adjusted models were restricted to 211 male or female respondents and included recruitment phase and institution; the complete-task model additionally included familiarity and all five task purposes.

Table S6: Institutional guideline visibility and formal policy demand by institution

Institution	<i>n</i>	Guidelines visible: Yes		%	Formal policies: Yes		%
Novi Sad	83	15	18.1		54	65.1	
Košice	72	23	31.9		48	66.7	
Warsaw	38	6	15.8		14	36.8	
Banská Bystrica	11	3	27.3		10	90.9	
Maribor	10	6	60.0		5	50.0	

Institutional guideline visibility: Cramer's $V = 0.191$, permutation $p = 0.047$, Holm $p = 0.047$. Formal policy demand: $V = 0.226$, permutation $p = 0.005$, Holm $p = 0.009$. Small-site percentages are unstable and institution overlaps with country, phase, and program mix.

Table S7: Core behavior, attitude, intensity, and policy associations

Analysis	Comparison	Effect	95% CI	<i>p</i>
Integrity-threat rating by complete-task behavior	Yes vs No; median 4 (3–4) vs 4 (3–5)	$r = -0.208$	–0.352––0.061	0.006
Use frequency by complete-task behavior	Yes vs No; median 4 (3–5) vs 3 (2–4)	$r = 0.321$	0.186–0.460	< 0.001
Policy support by guideline visibility	77.4% vs 55.9%	OR 2.70	1.32–5.51	0.006
Policy support by guideline visibility, adjusted	211 respondents	OR 2.73	1.23–6.08	0.014
Integrity-threat agreement by complete-task behavior, adjusted	211 respondents	OR 0.78	0.42–1.44	0.424

Table S8: Complete-task generation by AI-use frequency

Frequency	Yes/ <i>n</i>	%	Wilson 95% CI
Never	0/2	0.0	0.0–65.8
Less than once a week	4/14	28.6	11.7–54.6
About once a week	5/25	20.0	8.9–39.1
2–4 times a week	31/68	45.6	34.3–57.3
5–6 times a week	17/41	41.5	27.8–56.6
Every day	43/64	67.2	55.0–77.4

Table S9: AI-use purposes and complete-task generation

Purpose	Selected %	Unselected %	Crude OR	Adjusted OR (95% CI)	Holm <i>p</i>
Solving problems	50.9	31.1	2.29	1.39 (0.60–3.22)	0.889
Programming	56.0	25.0	3.82	2.94 (1.35–6.40)	0.046
Teaching	57.4	38.3	2.17	2.54 (1.29–5.02)	0.046
Writing homework/tasks	74.6	35.1	5.43	2.82 (1.20–6.62)	0.088
Writing essays	72.5	38.7	4.20	1.03 (0.40–2.67)	0.947

Displayed Holm p values refer to the seven-term adjusted complete-task model family (frequency, familiarity, and five purposes). Crude within-purpose results are available in the accompanying workbook.

Table S10: Preferred treatment of AI-assisted dishonesty (item AB)

Preference	Overall %	Complete-task %	Other %	OR (95% CI)	Holm <i>p</i>
Strict penalty	10.7	5.0	15.8	0.28 (0.10–0.79)	0.070
Better policies and awareness	36.9	23.0	49.1	0.31 (0.17–0.56)	< 0.001
Shift in learning and assessment	43.0	38.0	47.4	0.68 (0.39–1.18)	0.852
Similar to other cheating	21.0	22.0	20.2	1.12 (0.58–2.16)	0.934
Adapt rather than punish	44.9	49.0	41.2	1.37 (0.80–2.35)	0.852
Not a serious issue	16.8	19.0	14.9	1.34 (0.65–2.74)	0.934

Table S11: Detection awareness and complete-task generation

Awareness item	Aware %	Unaware %	Crude OR (95% CI)	Holm <i>p</i>
Plagiarism-detection software	48.9	29.2	2.33 (0.92–5.87)	0.166
AI-detection tools	48.6	37.1	1.60 (0.76–3.37)	0.267

Adjusted odds ratios were 2.23 (95% CI 0.81–6.11; Holm *p* = 0.240) and 1.77 (0.77–4.06; Holm *p* = 0.240), respectively, after controlling for use frequency, gender, phase, and institution. Awareness was not associated with less complete-task generation.

SUPPLEMENTARY FIGURES

The remaining generated figures are provided below for transparency and reproducibility.

Key AI-use, learning, and governance outcomes

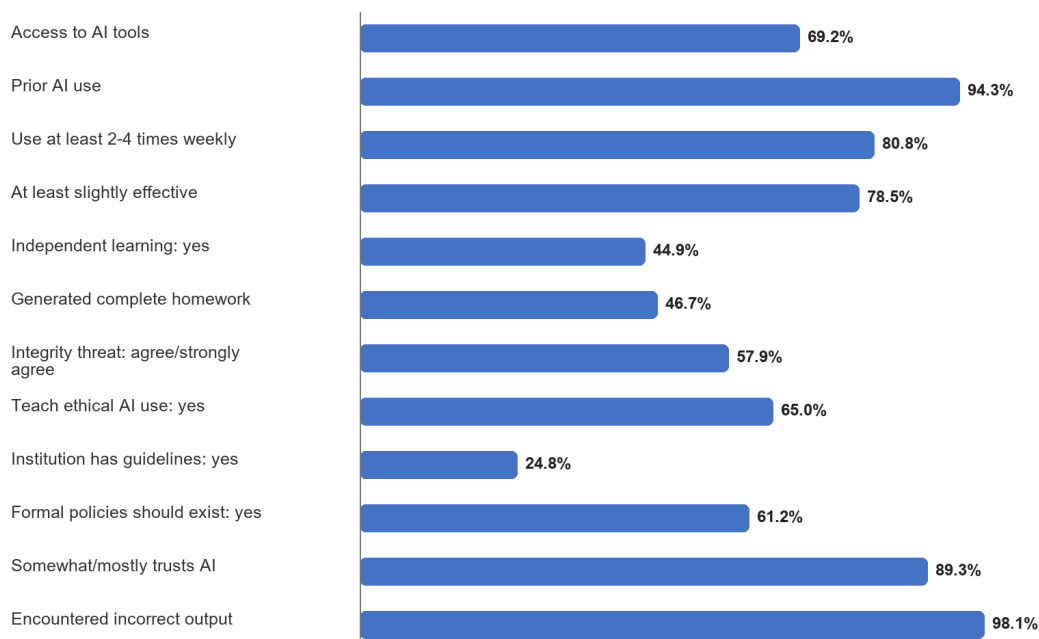


Figure S1: Key AI-use, learning, integrity, and governance outcomes. Percentages use item-specific denominators.

Participant distribution by institution

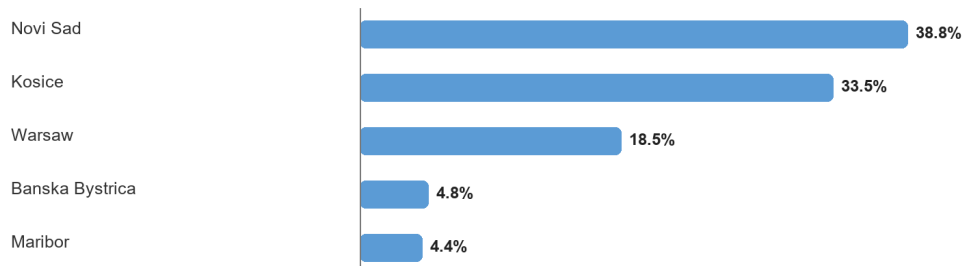


Figure S2: Unequal institutional composition of the convenience sample.

Educational tools and task purposes by gender

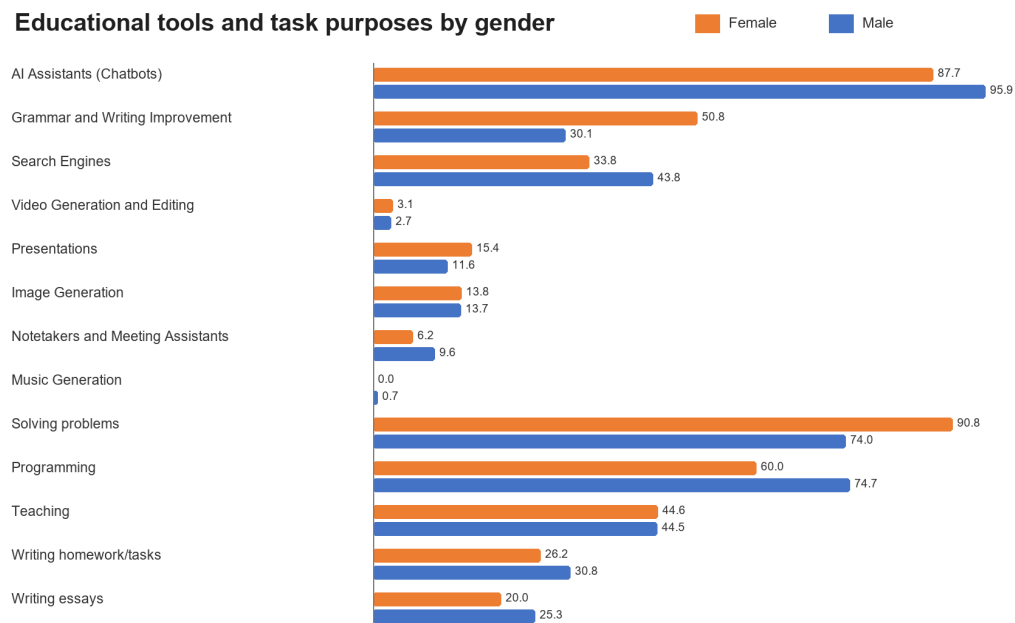


Figure S3: Educational-tool and task-purpose selections among male and female AI users. Inferential results are reported in Tables 2 and 3.

Adjusted gender sensitivity models

Odds ratio for female versus male; adjusted for phase and institution

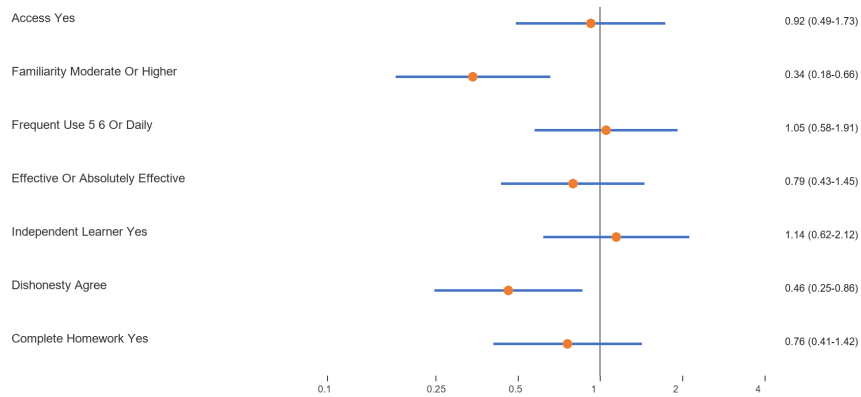


Figure S4: Adjusted odds ratios for female versus male respondents. Models adjust for recruitment phase and institution.

Primary ordinal gender comparisons

Rank-biserial correlation; positive values indicate higher female ranks

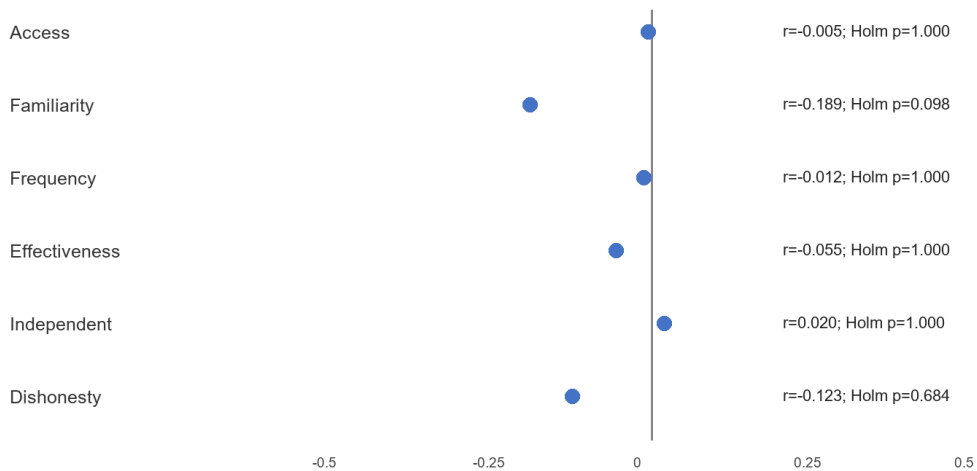


Figure S5: Rank-biserial effects for the six primary ordinal gender comparisons. Positive values indicate higher female ranks.

Perceived academic-integrity threat by complete-task behavior

Distribution of perceived academic-integrity threat within complete-task-generation groups

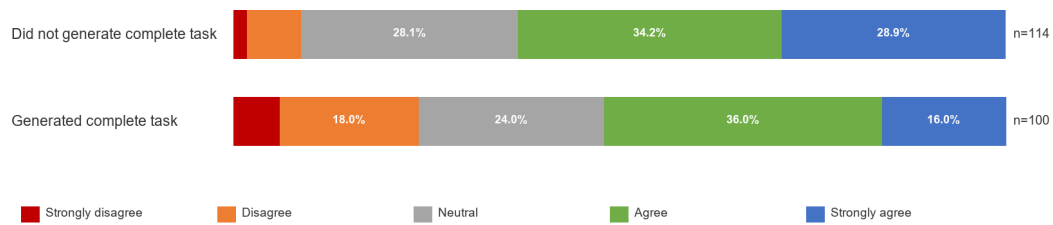


Figure S6: Integrity-threat response distribution according to complete-task behavior.

Detection awareness and complete-task behavior

Percent reporting complete-task generation

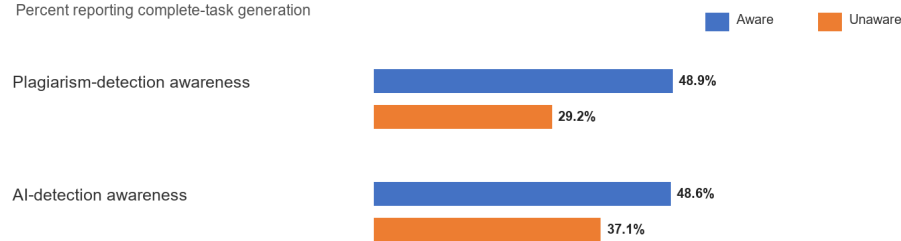


Figure S7: Complete-task behavior by awareness of plagiarism- and AI-detection tools.

Adjusted associations with complete-task generation

Odds ratios adjusted for all displayed variables, gender, phase, and institution

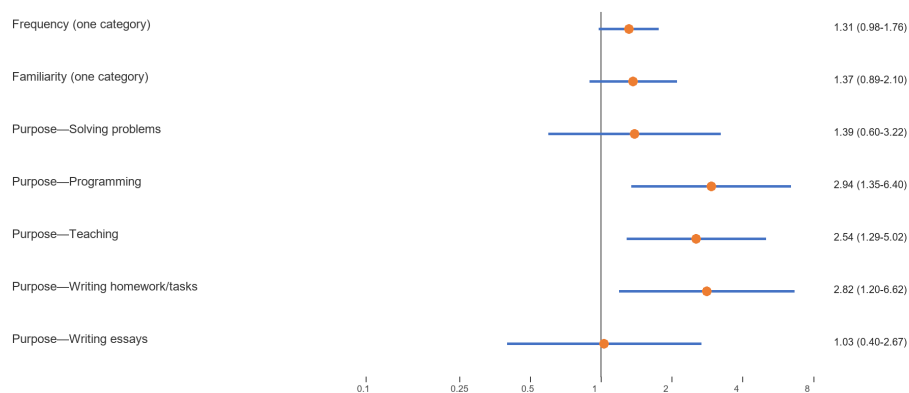


Figure S8: Adjusted associations of use intensity and task purposes with complete-task generation.