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Artificial Intelligence in Higher Education: Students' Artificial Intelligence Use and its Influencing Factors

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Abstract

This study is part of a larger research project that examines the impact of the spread of artificial intelligence (AI), especially ChatGPT and similar generative AI tools on Hungarian higher education. In this paper, we investigate the use of AI (in terms of awareness, tools used, areas of use, and barriers to use) and factors influencing its use in the studies of Hungarian university students, especially those studying in the fields of humanities, social sciences, and teacher education. A large-sample empirical study of 1,027 students revealed significant differences in the use of AI tools by course type, gender, educational level, and field of study. Areas of use and barriers to use are significantly influenced by course type and gender, whereas the level of knowledge is considerably influenced by course type. The results of our study can support higher education institutions in developing strategies to promote the ethical use of AI tools and to integrate them into educational processes while ensuring equal access for all students.

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Practitioner Notes

1. Full-time students are more exposed to AI concepts and use AI tools more extensively than correspondence students.
2. Correspondence students, balancing work and family responsibilities, are more open to using AI tools. However, they face barriers such as a lack of AI knowledge and access to technical tools.
3. Men tend to use a wider variety of AI tools and more experimental with AI technology, while women express more concerns and barriers related to AI use.
4. Students in the humanities and social sciences use AI tools more than students in teacher education, with notable differences in the types of AI tools used.
5. Undergraduate students, especially those in the first year, generally have lower exposure to AI tools due to their recent transition from secondary education.

Keywords

Artificial Intelligence, Higher Education, Academic Integrity, AI

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Introduction

The role of AI in education has received increased attention with the release and rapid adoption of ChatGPT and similar generative AI (genAI) applications by the end of 2022. University students have also been quick to explore the potential of this tool. This is evidenced by the fact that since ChatGPT was made available to the general public on 30 November 2022, 128,402 visits to the ChatGPT site were recorded from the eight leading UK university Wi-Fi networks alone in December 2022. By January 2023, this figure had risen to 982,809, indicating the software's popularity (Snepvangers, 2023).

According to various surveys, in 2023 ─ the year immediately preceding the present survey ─ the vast majority of Hungarian university students were already familiar with AI and nearly 80% of them had used some AI tool in their studies (HR Portal, 2023; Rajki et al., 2024). The data indicated the student demand for the use of these tools. The potential of the widespread use of AI tools means that AI skills will become indispensable in many areas of the labour market (Green, 2024), which will have some impact on all higher education institutions. The sudden changes will require a rapid response from higher education institutions, education professionals and academics.

The very rapid proliferation of genAI applications has raised awareness not only among users but also among researchers about the effects of AI on social and economic life. Empirical research on the impact of AI on higher education has covered, among other things, the use of AI tools by university students (Chan & Hu, 2023; Delcker et al., 2024; Folmeg et al., 2024; Kanont et al., 2024), the potential of using genAI tools in (higher) education (Essien et al., 2024; Fekete et al., 2024; Grassini 2023), and the possibility of filtering out unethical use (Cotton et al., 2024).

In higher education, institutions serve as foundational structures, establishing guidelines and recommendations. However, bridging these frameworks with actionable proposals relies heavily on educational professionals. Central to this endeavour is understanding the emotional, cognitive, and behavioural attitudes towards AI held by key stakeholders: teachers and students. This study focuses on assessing university students' attitudes towards AI, pivotal for institutions and educators considering AI integration in education. It emphasises the diversity among students, influenced by demographic factors like gender, educational background, and field of study. By identifying these influences, our research aims to equip educators and institutional leaders with insights crucial for fostering inclusive AI adoption in disciplines such as social sciences, humanities, and pedagogical fields.

Literature

Integrating Artificial Intelligence (AI) into higher education is transforming the landscape of higher education, creating new opportunities in teaching and research. Technologies such as intelligent tutoring systems, automated assessment, and personalised learning platforms (Sajja et al., 2023; Nguyen et al., 2024; Silva-Cornejo et al., 2024) are enhancing the effectiveness of education and improving students' learning outcomes (Fadlelmula & Qadhi, 2024; Pang et al., 2024). However, challenges also arise, including ethical concerns (Cotton et al., 2024), data privacy issues (Pang et al., 2024; Nguyen et al., 2024), the digital divide—which can deepen educational inequalities (Pang et al., 2024; Møgelvang et al., 2024; Nguyen et al., 2024)—and the risk of excessive technological dependence (Møgelvang et al., 2024; Delcker et al., 2024). Students' attitudes

towards AI can be influenced by various factors, including gender (Møgelvang et al., 2024), educational level, field of study, form of education, as well as ethical, effectiveness, and data privacy considerations. While research examines the impact of AI on student engagement and performance, little attention is paid to how different demographic groups use these tools. A deeper understanding of the application of AI in higher education is crucial to making educational practices fair and effective.

Gender differences in AI use

Gender differences in technology use and attitudes also extend to genAI, according to recent research (Møgelvang et al., 2024). Men use genAI tools more often and show more use (Møgelvang et al., 2024; Stöhr et al., 2024; Ofosu-Ampong, 2023; Fihris et al., 2024). An enhanced level of involvement with AI apps may be attributed to the fact that male students appear to be more comfortable using technology than female students (Møgelvang et al., 2024; Stöhr et al., 2024; Fihris et al., 2024). Because students who are more familiar with technology are more likely to use AI technologies efficiently, this participation gap may affect the overall success of AI in educational contexts (Delcker et al., 2024). In addition, female students might be less willing to integrate these technologies into their coursework since they are more concerned about the ethical ramifications of artificial intelligence (Stöhr et al., 2024; Fihris et al., 2024).

To guarantee that all students, regardless of gender, can utilise these technologies effectively, the integration of AI literacy across numerous topics is necessary (Folmeg et al., 2024; Nguyen et al., 2024). Based on the literature, we formulated our first hypothesis:

H1: Male students are more likely to use AI than females.

Education differences in AI use

The level of education influences students' interactions with AI and attitudes towards AI (Stöhr et al., 2024; Arowosegbe et al., 2024). Graduate students (MA and PhD) are more likely to engage with AI tools than undergraduate students (Arowosegbe et al., 2024; Strzelecki & ElArabawy, 2024). This tendency can be linked to their advanced research requirements and the complexity of their academic tasks, which frequently necessitate sophisticated AI systems for data analysis and feedback (Pang et al., 2024; Arowosegbe et al., 2024). For example, AI can deliver personalised learning experiences, which are especially advantageous for graduate students who demand individualised assistance with their studies (Fadlelmula & Qadhi, 2024). Studying the attitudes of students in the fields of economics and business management and education showed that the perception of the benefits of AI in their profession becomes greater as students advance in their undergraduate and graduate studies. The majority also think that AI training will be beneficial or very beneficial for their careers (Almaraz-López et al., 2023).

Finally, students' engagement with AI is substantially influenced by their academic discipline. Møgelvang & Grassini (2024) found that students in the Faculty of Engineering and Science as well as the Faculty of Economics and Social Sciences showed more positive attitudes towards AI than students in the Faculty of Health Sciences or the Faculty of Teacher Education, Culture and Sport Sciences. Research by Stöhr et al. (2024) shows that like medical students, humanities and arts students have a reserved and sceptical attitude towards AI compared to science and engineering students. Students in the social sciences were found in between the two large groups. AI is integrated into students' studies in different ways in different fields of study. In the social

sciences, AI can revolutionize data analysis and questionnaire development, providing deeper social insights, but it requires human oversight due to ethical challenges such as bias and underrepresentation of certain groups (Nath et al., 2024; Gilardi et al., 2024; Bail, 2024). In the humanities, AI serves as a research tool and a subject of investigation, analyzing complex human questions (Samartoiy & Davar, 2023). Resistance from disciplinary traditions, ethical concerns and the limited relevance of AI in their learning processes may explain the reluctance and scepticism of humanities students towards AI. (Stöhr et al., 2024). In teacher education, generative AI opens up new pedagogical possibilities while encouraging ethical reflection and critical evaluation of educational integration (Creely & Blannin, 2023). At the same time, the less positive attitudes towards AI among teacher trainees may be explained by their concern about the loss of knowledge and skills of students due to the uncritical use of generative AI (Møgelvang & Grassini (2024).

These variations highlight how disciplinary needs and technological exposure shape students' engagement with AI, balancing opportunities with critical oversight-education (full-time or correspondence). However, as the age of the users of the two types of education in Hungary is typically different, with older age groups studying in correspondence courses while working, age-related studies may be relevant. The results of studies on this are contradictory: while some have shown age-related differences in AI use (Rahman et al., 2025; Chan & Lee, 2023; Tin et al., 2024; Bokor et al., 2022; Møgelvang & Grassini 2024), others have not (Khater et al., 2023; Kaya et al., 2024). In light of this, testing our (H2) hypothesis is of particular importance.

Based on the literature, we formulated the following hypotheses:

H2: Full-time students are more likely to use AI than correspondence students.

H3: Students in the humanities and social sciences are more likely to use AI than students in teacher education.

H4: MA and higher degree students are more likely to use AI than BA students.

Method

Procedure

During the sampling, we approached those higher education institutions at the institutional and departmental level, where undergraduate, master's, or PhD programs are conducted in the fields of humanities, social sciences, and teacher education, on full-time or correspondence courses. We tried to reach the students via email or Facebook, with the help of department and institute leaders related to the courses. The online questionnaire was available on Survio.com between 14 September 2023 and 14 October 2023. Rajki's (2023) study provided the theoretical framework for our self-designed questionnaire, which discusses versatile applications and impacts of AI in education, highlighting both ethical and societal challenges. The questionnaire contained 27 questions, with three open-ended and 24 closed-ended questions.

Ethical review and approval were waived for this study due to the following reasons: All students were invited to participate in the study via email or Facebook, with the help of department and institute leaders. All participants received a complete description of the study in the form of a participant information sheet. All students were informed that their participation in the online survey would be anonymous and voluntary and that they could quit the online survey

whenever they wanted without suffering any disadvantage. All participants were informed that the results of the present study would be published after completion of the project.

Sample

Our sample cannot be considered representative, but the large number of respondents (N=1027) allows us to draw some conclusions and correlations. Our questionnaire was completed by 1,201 people, of whom 1,027 were university/college students studying humanities, social sciences, or teacher education. Therefore, in the remainder of the study, only the data related to them will be presented and analysed in detail. 83.2% of our sample graduated at the bachelor's level, 11.1% at the master's level, 4.5% at the undivided level, and 1.3% at the PhD level. By field of education, 34.5% of students studied humanities, 43.7% in social sciences, and 21.8% in teacher education. In addition, 79.0% of respondents were female and 21.0% were male. The proportion of respondents who studied a modern language (11.3%), communication and media studies (13.4%), political science and international studies (11.3%), sociology (11.5%), psychology (11.1%) or pedagogy, teaching, or kindergarten teaching (19.8%) exceeded 10%.

Looking at the age distribution, more than half of the respondents (54.3%) were between 18 and 22 years old, 20.0% were between 23 and 30, and 25.7% were over 30. The distribution of full-time and correspondence students was 65.4% and 34.6%, respectively. In our sample, 37.3% did not work, 29.8% worked part-time, and 32.9% worked full-time during their university studies. The socio-demographic characteristics of the full-time (672 students) and part-time (355 students) student populations are summarised in Table 1.

Table 1

Socio-Demographic Comparison of Full-Time and Part-Time Students

Age	**Working while studying**	**Full-time(65,4%)**		**Correspondence (34,6%)**	
		Number of People	**Percentage**	**Number of People**	**Percentage**
18-22 years (54.3%)	**Full-time**	12	1.8	21	5.9
	Part-time	206	30.7	9	2.5
	Currently not working while studying	303	45.1	7	2.0
23-30 years (20.0%)	**Full-time**	22	3.3	59	16.6
	Part-time	64	9.5	9	2.5
	Currently not working while studying	46	6.8	5	1.4
31+ years (25.7%)	**Full-time**	10	1.5	214	60.3
	Part-time	5	0.7	13	3.7
	Currently not working while studying	4	0.6	18	5.1
Total		672	100.0	355	100.0

Table 1 illustrates that the majority of full-time students fall into two main categories*:* those aged 18-22 who are not employed during their studies (representing almost half, or 45.1%) and those of the same age group who are engaged in part-time work while studying (30.7%). In contrast, the percentage of students aged 30 and over is minimal. A significant proportion of correspondence students are either aged 30 and above (69.1%) or are engaged in full-time employment while studying (82.8%). However, due to the reasons previously stated, only the clerkship variable was incorporated into the model, excluding the age and employment variables.

Measures

In this research, we wanted to investigate the aspects of AI use listed below and measure them using the detailed variables. To test the concepts of (1) Extent of Awareness and (2) Sources of Awareness, participants were asked whether they had encountered the concept of AI in the four areas we wanted to investigate. The Extent of Awareness was measured by the number of domains, while Sources of Awareness were measured by the four binary variables corresponding to the four domains. To examine (3) the Extent of Tool Use and (4) Tools Used/Tried, we asked participants whether they had used the seven most popular AI-based tools we listed in their studies. The Extent of Device Use was measured by the number of AI tools used, while the Used/Tried Tools were examined using the seven binary variables corresponding to the seven tools. To measure (5) the Extent of Application Area and (6) Areas of Intended Use, participants were asked whether they would use an AI tool from the nine areas/objectives under study during their studies. Application area extent was measured by the number of places indicated, and Areas

of Intended Use were measured by the nine binary variables corresponding to the nine areas listed. Finally, to investigate the Amount of (7) Inhibiting Factors and the Inhibiting Factors, we asked participants whether the seven most common factors we listed inhibited their use of AI. The Amount of Inhibiting Factors was measured by the number of Inhibiting Factors indicated, while the Inhibiting Factors were examined using the seven binary variables corresponding to the seven factors.

Data analysis

The independent variables that we investigate are: type of education (1: full-time, 2: correspondence); type of work outside the university (1: full-time, 2: part-time, 3: not working); gender (1: male, 2: female); age (scale); level of education (1: bachelor, 2: master, master's, doctoral, PhD) and field of education (1: humanities, 2: social sciences, 3: teacher education). Comparisons between faculties and universities are not possible due to the composition of our sample. For the descriptive analysis of the variables under study, we provide item counts and frequencies (proportions). The effect of each independent variable on the scaling variables measuring the intensity of AI use – Extent of Awareness, Extent of Device Use, Extent of Application Area, and Amount of Inhibiting Factors – as dependent variables were examined by setting up multinomial logistic regression models. (Cross-tabulations were used to ensure that no combination of low-level variables were found where the number of cases did not exceed 5.). The relationship between each independent variable and the binary dependent variables – Sources of Awareness, Devices Used/Tried, Areas of Intended Use, and Inhibiting Factors – was tested using Pearson's chi-square test. Data processing was performed using IBM SPSS 28.0 software, and MS Excel was used to create the graphs.

Results

Logistic Regression Findings

The analysis was conducted using four multinomial regression models with the variables Extent of Awareness, Extent of Device Use, Extent of Application Area, and Amount of Inhibiting Factors as dependent variables. The explanatory variables were the type of education (1: full-time, 2: correspondence), gender (1: male, 2: female), level of education (1: bachelor’s, 2: master’s, undivided, PhD), and field of education (1: humanities, 2: social sciences, 3: teacher education). The variables were entered into the models using the enter method so that the explanatory variables had a combined effect. No confounding multicollinearity between variables was found (all VIF < 1.389). The inclusion of these variables resulted in an acceptable model, with the results of the Likelihood ratio chi-square test showing that the models are better predictors than the empty model without explanatory variables ($p < .001$ in all four cases). The effect size of the models is weak (Nagelkerke pseudo-R^2 indicators range from 6.0% to 16.3% (Table 2).

Table 2

Results of Multinomial Logistic Regressions

	Model 1: Extent of Awareness			Model 2: Extent of Device Use			Model 3: Extent of Application Area			Model 4: Amount of Inhibiting Factors		
Predictor	**Cat. 1 vs. Ref. OR (p)**	**Cat. 2 vs. Ref. OR (p)**	**Cat. 3 vs. Ref. OR (p)**	**Cat. 1 vs. Ref. OR (p)**	**Cat. 2 vs. Ref. OR (p)**	**Cat. 3 vs. Ref. OR (p)**	**Cat. 1 vs. Ref. OR (p)**	**Cat. 2 vs. Ref. OR (p)**	**Cat. 3 vs. Ref. OR (p)**	**Cat. 1 vs. Ref. OR (p)**	**Cat. 2 vs. Ref. OR (p)**	**Cat. 3 vs. Ref. OR (p)**
Gender (reference: Men)												
Women	1.34 (.17)	1.44 (.13)	0.68 (.11)	1.02 (.93)	.88 (.60)	.59 (.03)*	2.11 (.07)	2.55 (.02)*	1.92 (.09)	1.69 (.02)*	2.35 (.00)***	2.92 (.00)***
Type of Education (reference: Correspondence)												
Full-time	1.61 (.01)**	4.10 (0.00)***	8.61 (0.00)***	1.84 (.00)**	3.17 (.00)***	3.50 (.00)***	2.39 (.03)*	2.12 (.05)*	1.14 (.73)	.73 (.16)	1.56 (.07)	1.30 (.24)
Field of Education (reference: Teacher Education)												
Humanities	1.07 (.76)	1.71 (.05)	1.63 (.14)	1.33 (.20)	3.23 (.00)***	4.24 (.00)***	1.43 (.47)	1.33 (.53)	.80 (.63)	.79 (.41)	.60 (.10)	1.08 (.80)
Social-Science	.80 (.33)	1.32 (.32)	1.59 (.16)	1.51 (.07)	3.59 (.00)***	5.92 (.00)***	1.75 (.30)	2.06 (.16)	1.56 (.37)	.79 (.43)	.69 (.23)	.76 (.37)
Level of Education (reference: MA, Undivided, PhD)												
BA	1.58 (.06)	.93 (.77)	.52 (.01)*	.78 (.32)	.87 (.63)	.30 (.00)***	.38 (.13)	.39 (.13)	.42 (.16)	1.09 (.77)	.72 (.24)	.71 (.20)

Notes: OR = odds ratio; *$p < .05$**; $p < .01$; ***$p < .001$; **Model 1**: Nagelkerke $R^2 = .16$; **Model 2**: Nagelkerke $R^2 = .16$; **Model 3**: Nagelkerke $R^2 = .15$; **Model 4**: Nagelkerke $R^2 = .06$.

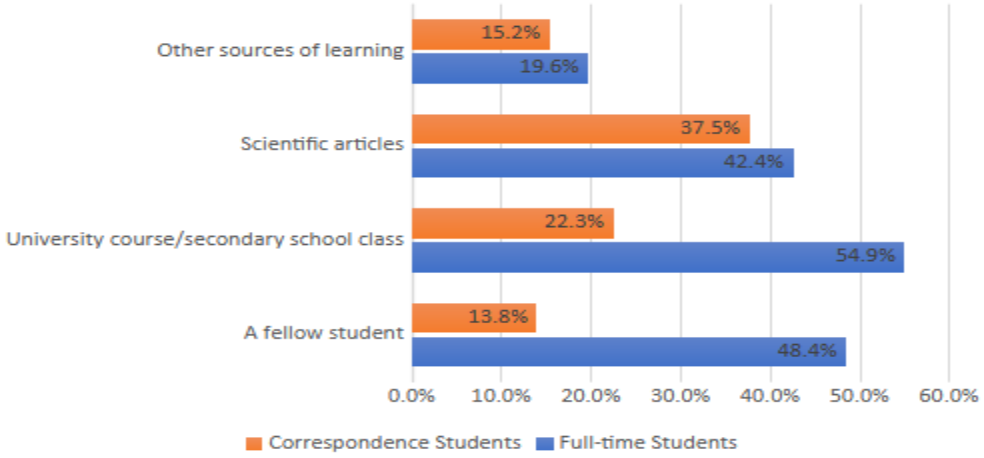
Type of Education as an Influencing Factor

Full-time students demonstrate a more extensive awareness of AI compared to correspondence students. According to Model 1 (Table 2), when controlling for other variables, full-time students were more likely to report exposure to AI across multiple categories: approximately one-and-a-half times more likely in one area (OR = 1.61), more than four times more likely in two areas (OR = 4.10), and over eight-and-a-half times more likely in three or more areas (OR = 8.61).

Differences in sources of AI-related information are presented in Figure 1. Full-time students significantly more often receive information about AI from fellow students ($\chi^2 = 119.82$, df = 1, $p < .001$) and university or secondary school courses ($\chi^2 = 100.73$, df = 1, $p < .001$). Conversely, reliance on scientific articles and other learning resources showed no significant difference between the two groups, suggesting that peer interactions and structured educational settings primarily account for the higher AI awareness observed among full-time students.

Figure 1

Correlation Between Each Information Area and the Type of Education

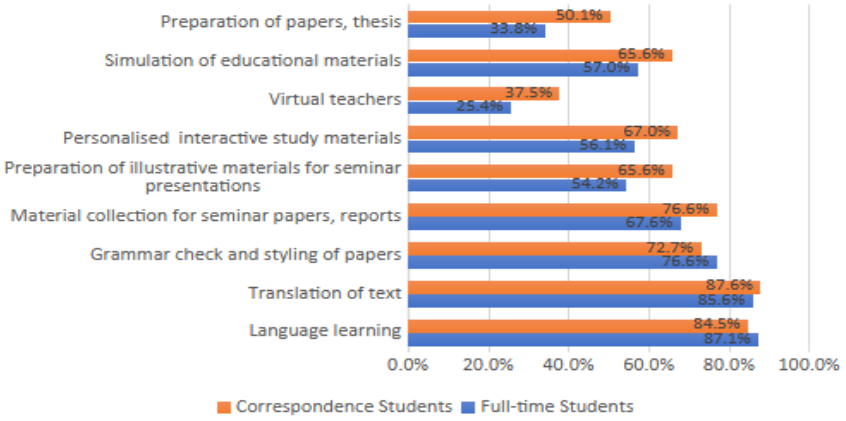


Model 2 (Table 2) further indicates that full-time students tend to utilize AI tools more extensively compared to their correspondence counterparts, although the differences in usage across various numbers of AI devices (one device OR = 1.84; two devices OR = 3.17; three or more devices OR = 3.50) were not statistically significant. Analysis of individual AI tools shows significant differences between the groups: full-time students more frequently use ChatGPT ($\chi^2 = 56.21$, df = 1, $p < .001$), DeepL ($\chi^2 = 22.54$, df = 1, $p < .001$), Grammarly ($\chi^2 = 36.09$, df = 1, $p < .001$), Duolingo ($\chi^2 = 44.97$, df = 1, $p < .001$), and Scholar AI ($\chi^2 = 9.27$, df = 1, $p = .002$). In contrast, correspondence students are significantly more likely to use Google Bard ($\chi^2 = 6.14$, df = 1, $p = .013$). No significant differences were observed for Bing Chat.

Model 3 (Table 2) reveals that full-time students are approximately twice as likely as correspondence students to desire the use of AI across multiple educational areas compared to none (OR = 2.39 for areas 1-3; OR = 2.12 for areas 4-6). However, no significant difference emerges between the groups when considering preferences for using AI in seven or more areas. Interestingly, despite full-time students' apparent higher affinity for AI, Figure 2 shows that correspondence students expressed significantly greater interest in using AI in six of the nine educational applications surveyed. These applications include: collecting materials for seminar papers and reports ($\chi^2 = 9.20$, df = 1, $p = .002$), preparing seminar presentations and illustrative materials ($\chi^2 = 12.55$, df = 1, $p < .001$), personalized interactive learning materials ($\chi^2 = 11.58$, df = 1, $p < .001$), virtual teachers ($\chi^2 = 16.10$, df = 1, $p < .001$), simulation teaching materials ($\chi^2 = 7.22$, df = 1, $p = .007$), and preparing dissertations and theses ($\chi^2 = 26.03$, df = 1, $p < .001$). None of the educational applications listed were more prevalent among full-time students.

Figure 2

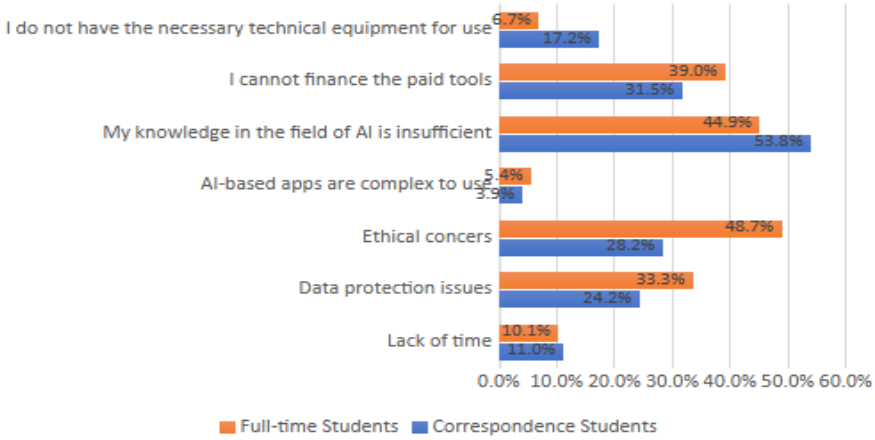
Correlation Between the Different Fields of Application and Type of Education



Regarding barriers to AI usage (Table 2), no overall significant difference emerged between the two student groups. However, when examining individual inhibiting factors (Figure 3), significant differences were identified in five of the seven factors analyzed. Correspondence students were notably more likely to cite lack of knowledge about AI ($\chi^2 = 7.31$, df = 1, $p = .007$) and absence of necessary technical tools ($\chi^2 = 27.60$, df = 1, $p < .001$) as barriers. Additionally, correspondence students were less likely to be inhibited by privacy issues ($\chi^2 = 9.14$, df = 1, $p = .002$) and ethical concerns ($\chi^2 = 40.16$, df = 1, $p < .001$). Conversely, full-time students more frequently reported financial constraints related to paid tools as a barrier ($\chi^2 = 5.55$, df = 1, $p = .018$).

Figure 3

Relationship Between Each Inhibiting Factor and Type of Education



Gender as an Influencing Factor

Based on multinomial logistic regression models, significant gender differences were also identified regarding inhibiting factors, AI device usage, and preferred AI application areas. Model 4 (Table 2) demonstrates that women report a greater number of inhibiting factors compared to men: they were more likely to experience inhibitions related to AI usage, with likelihood increasing progressively for one (OR = 1.69), two (OR = 2.35), or three or more (OR = 2.92) inhibiting factors.

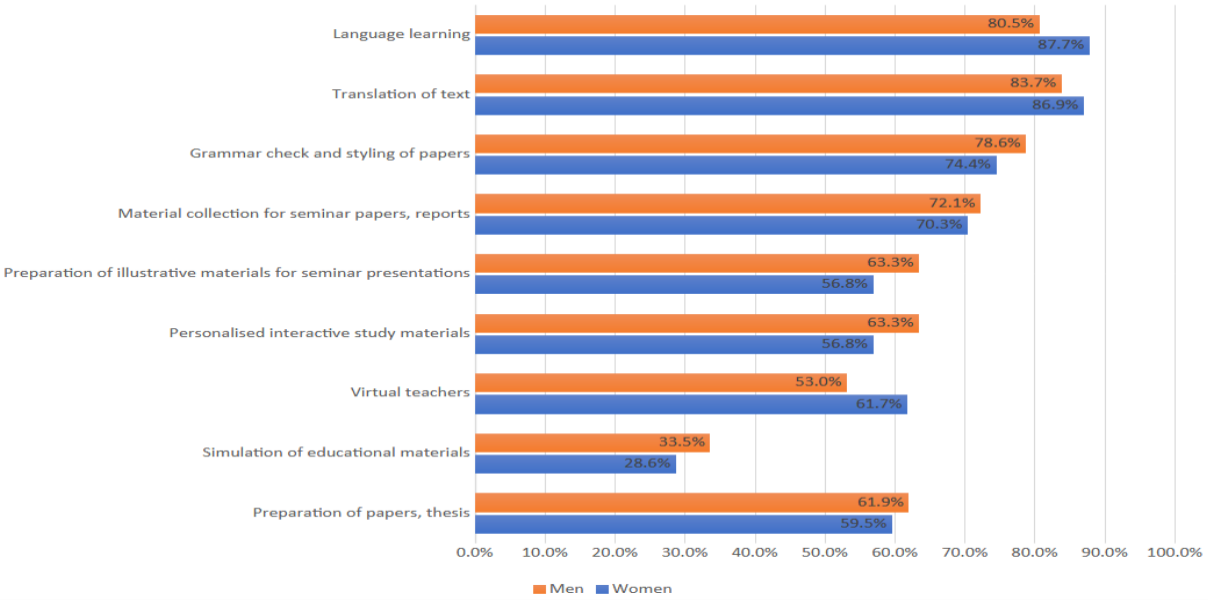
Specifically, women were significantly more likely than men to cite a lack of AI knowledge (χ^2 = 34.41, df = 1, p < .001) and insufficient access to technical tools (χ^2 = 5.37, df = 1, p = .021). Consequently, female students expressed greater perceived needs for additional knowledge and tools for responsible AI use.

Model 2 (Table 2) further shows gender disparities in actual AI tool usage, indicating men generally use a wider variety of AI devices. Women, controlling for other factors, were significantly less likely than men to have used three or more AI devices (OR = 0.59). Men were notably more frequent users of ChatGPT (χ^2 = 39.08, df = 1, p < .001), Google Bard (χ^2 = 5.78, df = 1, p = .016), Bing Chat (χ^2 = 44.43, df = 1, p < .001), and DeepL (χ^2 = 6.61, df = 1, p = .010). Although women were more inclined to use Duolingo, this difference was not statistically significant. Similarly, no significant gender differences emerged for the usage of Scholar AI and Grammarly.

Model 3 (Table 2) reveals that women have more extensive intended use of AI compared to men, with women being more than twice as likely (OR = 2.55) to aim for AI utilization in two areas versus none, controlling for other variables. Further analysis of gender differences in desired AI use (Figure 4) indicates that women are significantly more inclined to use AI tools for Language Learning (χ^2 = 7.44, df = 1, p = .006), while men show a stronger preference for Personalised Interactive Learning Materials (χ^2 = 5.33, df = 1, p < .001).

Figure 4

Correlation Between Application Areas and Gender



The Field of Education as an Influencing Factor

The field of education also influences AI usage. Students from humanities and social sciences fields report significantly more extensive use of AI devices than those in teacher education. According to Model 2 (Table 2), compared to teacher education students, those in humanities were twice as likely to use AI tools in two areas and three times as likely in three or more areas,

with respective odds ratios of 3.23 and 4.24. Similarly, students from social sciences had even higher likelihoods, with odds ratios of 3.59 and 5.92, respectively.

There were notable differences in specific AI tool usage across educational domains. ChatGPT ($\chi^2 = 88.94$, df = 2, $p < .001$) and Duolingo ($\chi^2 = 20.59$, df = 2, $p < .001$) were more extensively used by social sciences students and less so by teacher education students. Similarly, humanities students significantly preferred Deepl ($\chi^2 = 36.37$, df = 2, $p < .001$) and Grammarly ($\chi^2 = 21.93$, df = 2, $p < .001$) compared to those in teacher education. Conversely, teacher education students showed a non-significant tendency towards using Google Bard more frequently than their counterparts in other fields. No significant field-specific differences were observed for Scholar AI and Bing Chat.

The Level of Education as an Influencing Factor

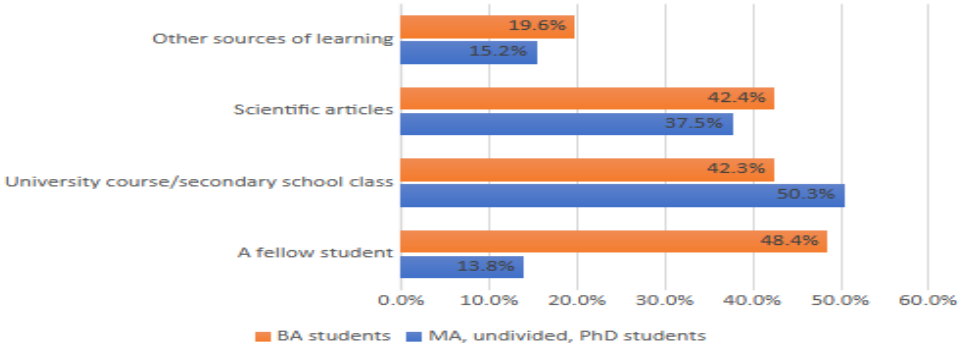
Models 1 and 2 indicate that the educational programs examined – Bachelor's versus Master's, undivided training, and PhD – differ in the extent of AI awareness and tool usage. Students enrolled in a Master's or PhD program demonstrate both broader awareness and greater tool use. After controlling for other variables (Table 2), these students are nearly half as likely (OR=0.52) to have encountered AI in at least three areas compared to those without such exposure, and they are roughly one-third as likely (OR=0.30) to be using three or more AI devices versus none.

Figure 5 illustrates additional variations in AI-related knowledge sources by level of education. Undergraduate students rely significantly more on other study resources ($\chi^2 = 7.52$, df = 1, $p = .006$) and peer interactions ($\chi^2 = 6.75$, df = 1, $p = .009$) than those in advanced programs. In contrast, using university courses as a primary source of AI information – a choice more frequently reported by Master's, undivided training, and PhD students – does not yield a statistically significant difference.

Moreover, students in Master's, undivided training, and PhD programs are significantly more likely to use Bing Chat ($\chi^2 = 4.11$, df = 2, $p = .043$), Deepl ($\chi^2 = 40.66$, df = 1, $p < .001$), Grammarly ($\chi^2 = 7.449$, df = 2, $p = .006$), and Scholar AI ($\chi^2 = 21.26$, df = 2, $p < .001$) than undergraduate students. No significant differences were detected for Duolingo, Google Bard, or ChatGPT.

Figure 5

Correlation Between Each Information Area and Level of Education



Discussion

The main objective of this research was to identify the factors that most influence the use of AI in the studies of students in the humanities, social sciences, and teacher education. Four research hypotheses were formulated to investigate the influence of type of education, gender, field of education and level of education. The main findings of this research are as follows:

Verified Main Gender differences in AI use

Men are more likely to use AI devices (i.e. more than one type of device) and have tried more of the devices we surveyed than women. However, the (desired) scope of AI use is more extensive for women than for men. Of the areas we examined, we found differences in language learning and personalised interactive learning materials, with the former being more desired by women and the latter by men.

Women are more likely to have several factors that inhibit the use of AI. Analysing the factors we examined one by one, we found that lack of knowledge of AI and lack of technical tools are more likely to occur in women. Due to the numerous gender differences in the use of AI, hypothesis H1 “Male students are more likely to use AI than females” is accepted. Several studies examining gender differences in AI use have found similar results (Howington, 2023; Møgelvang et al., 2024; Møgelvang & Grassini, 2024; Stöhr et al., 2024; Ofosu-Ampong, 2023; Fihris et al., 2024).

The reason behind this, according to an AI expert (Costa, 2023), is that the fields of science, technology, engineering, and mathematics have traditionally been dominated by men, and the skills needed to use AI are rooted in their use. Consequently, women are less confident in using AI tools. Although many AI-based tools do not require technical skills, many women do not consider themselves technically skilled enough to experiment with them. On the other hand, AI is still seen by many people as being in the world of science fiction, which is traditionally a male domain. In addition, there are psychological reasons: the typical thinking and behaviour of women also discourage them from using AI: women tend to start using a tool only when they have a high level of related skills. In contrast, men are willing to experiment even without expertise (Costa, 2023). However, it is also important to note that there are research reports in the literature where there was no significant difference between the two genders (Arowosegbe et al., 2024; Iddrisu et al., 2025).

Verified educational differences in AI use

Full-time students have been exposed to the concept of AI more widely (in more areas) than correspondence students. In terms of resources, we found that full-time students were more likely to be informed by a peer and by university course material than correspondence students. Full-time students are also more likely to have used AI tools more extensively, i.e., they have tried/used more AI tools during their studies.

The above results may be explained by the fact that 77.6% of full-time students belong to the younger age group of 18-22 years (while the share of those aged 30+ is negligible) and the high share of those not working while studying (45.1%) and those in the same age group working part-time while studying (30.7%). In contrast, among correspondence students, the proportion of those over 30 years old (69.1%) and those working full-time alongside their studies (82.8%) is very high. Relationship issues were excluded from the questionnaire; however, the age distribution means

that the proportion of students in long-term relationships, married or with children, may be significantly higher among correspondence students. As a result, they are likely to have much less time than their full-time counterparts to immerse themselves in their studies and explore new technological opportunities related to their studies. In addition, due to the lower number of hours, they have less contact with the educational institution and less contact with each other and their teachers, which may result in their being less informed about new developments and challenges in their studies, especially at the beginning of the semester, and less able to obtain relevant information from each other and their teachers. Therefore, these factors may have an impact on their attitudes toward, sources of information, and experiences with AI tools.

In the case of full-time students, the (desired) field of application of AI is also more extensive (i.e. full-time students use AI tools in more areas during their studies), but several of the desired fields of application we examined (such as the collection of materials, the preparation of presentations, illustrative material, personalised interactive learning materials, virtual teachers, simulation teaching materials and the preparation of essays and theses) were indicated by a higher proportion of correspondence students than full-time students. The sociodemographic characteristics of correspondence students, as previously described, may account for their openness. Specifically, a substantial portion of these students balance university studies with work and family responsibilities, significantly complicating their lives. Conversely, their limited participation in higher education hinders their ability to assimilate acquired knowledge. They are receptive to any assistance that facilitates the fulfilment of their academic obligations. Furthermore, a knowledge deficit is evident in many of their responses. The necessity for education on the ethical utilisation of AI is underscored by the fact that half of the respondents in correspondence courses would employ AI tools for the preparation of papers and theses.

No differences were observed in the number of barriers to AI use between the types of Education. However, when examining the individual barriers, it was discovered that the correspondence students were more hindered by their lack of knowledge of AI and the lack of technical tools to use it than the full-time students. This may be due to the generational factors mentioned earlier. Full-time students have a higher proportion of 18-22-year-olds who are more up-to-date, probably with financial support from their parents.

Privacy, ethical concerns, and the inability to finance paid tools are more prevalent among full-time students. For full-time students, more sensitive privacy and ethical concerns may also occur because they have a more intensive relationship with the educational institution and teachers, possibly building stronger loyalty and more time to immerse themselves in the relevant literature, thus having a better understanding of the issues involved in the use of AI tools. The majority of full-time students have a more limited income compared to their correspondence peers (52.5% are not working compared to only 8.5% of correspondence students), so there is a correspondingly higher proportion of those who found it problematic to subscribe to premium AI tools.

For several aspects of AI use, we identified differences in the type of education, and therefore hypothesis H2 “Full-time students are more likely to use AI than correspondence students” was accepted. Key Findings and Conclusions in the Students in the humanities and social sciences use more AI tools than students in teacher education. Notable differences are that more students in the social sciences (compared to students in teacher education) have used ChatGPT and Duolingo, while more students in humanities (compared to students in teacher education) have

used Deepl and Grammarly. The above results may be explained by the fact that many of the students in the sample in the field of teacher education are studying for a degree in preschool teacher education and teacher training, where the age range may make the presence of AI in the curriculum and teaching less prominent. In addition, the requirements of the other two fields of study have a stronger demand for foreign language use: among the humanities graduates in the sample, there is a high proportion of modern foreign language majors (31.3%), as well as a high proportion of psychology majors (31.6%), where foreign language requirements are also quite high.

These partial results are partially consistent with the findings of Møgelvang & Grassini (2024), Stöhr et al. (2024), Nguyen et al. (2024), and Zhou et al. (2024). And, although differences were found in the field of education for the Extent of Device Use and Used/Tested Tools, no differences were found for the other aspects of AI use examined. Thus, hypothesis H3, "Students in the humanities and social sciences are more likely to use AI than students in teacher education", is only partially accepted. This area needs further investigation.

Master's, undivided training, and PhD students also have a wider range of knowledge and tools. Among the various sources of information examined, other sources of learning and peers as sources of information are more prevalent among bachelor's students than undivided training, master's, and PhD programs. Among the tools we have examined, Bing, Deepl, and Grammarly have been used more by undivided, Master' and PhD students than by their undergraduate counterparts. This is similar to the results obtained by Arowosegbe et al. (2024) and Strzelecki & ElArabawy (2024) in their study of the effect of level of education.

However, in the analysis, it is worth bearing in mind that 58.6% of the undergraduate students were first-year students, so most of them are likely to be recent high school graduates. Due to the requirements of secondary school, they probably did not have access to AI tools before, and probably not during their university studies, as the data were collected in the first weeks of the first semester in autumn 2023. Differences were found in the Extent of Awareness, Sources of Awareness, Extent of Device Use and Used/Tested Tools in the level of education. No differences were found for the other aspects of AI use examined. Thus, hypothesis H4, "MA and higher degree students are more likely to use AI than BA students", is only partially accepted. This area requires further investigation.

Conclusions

The findings of our research indicate that there are differences between certain groups of students (by type of education, gender, level of education, and field of education) in terms of awareness, the tools used, the areas of use, and the barriers to use. It is of paramount importance to consider these findings when deepening the integration of AI tools in higher education, adapting and developing educational frameworks, and addressing ethical and privacy concerns (formulating strategies and recommendations, and integrating them into curricula). This will ensure that all student groups are fully aware of the expectations and challenges related to the responsible use of tools. Furthermore, our findings can inform the development of strategies to enhance technological access and equal opportunities (e.g., support for student groups facing financial constraints). The research findings can offer significant insights for future educational advancement, technological investment, and equitable opportunities across both genders and types of education.

Firstly, these differences provide an opportunity for higher education institutions to develop targeted strategies to better integrate AI tools into the learning process. For example, if certain groups of students are less aware of the potential of AI, specific training, workshops and outreach programs can be organised for them. This can reduce the information gap and increase equal opportunities among students.

Secondly, identifying differences can help educators and university policymakers to develop tailored teaching methods and curricula. If, for example, the use of AI is less widespread in certain fields of study (e.g. humanities) and more common in others (e.g. computer science), institutions may consider introducing AI-based tools in traditionally less-affected fields. Third, identifying barriers can help universities to plan targeted interventions. For example, if the main barrier is the lack of technological background, institutions can invest in infrastructure development. And if student attitudes or lack of confidence are the barrier, awareness-raising campaigns and demonstrations of good practice can be a solution. Finally, the results of this research can contribute to making higher education institutions more competitive in the digital age. Promoting the use of AI can not only improve the learning experience of students but also increase the quality and efficiency of education. Institutions can also better adapt to the needs of the labour market, as learning to use AI tools is a key skill for the future labour market.

Overall, therefore, the identification of differences offers the opportunity to further improve higher education systems, increase inclusiveness and better disseminate AI-based learning solutions, thereby enabling students to become more successful and better-prepared professionals in the digital age.

Limitations and Future Research Directions

A limitation of the research is that the sampling was non-random, so our results were not necessarily representative of a wider population. Furthermore, the online questionnaire may have introduced bias: its implementation could influence the demographic mix of respondents, potentially due to technical affinity or accessibility, although the latter is diminishing in significance as technology proliferates. Self-reporting can lead to a self-selection effect, which can distort the results: it can over-represent those who are heavy AI users or those who are strongly against AI. Other drawbacks include the predefined response options used in the questionnaire, which may have influenced respondents. A further limitation is that the research was conducted using only quantitative methods, qualitative aspects of the research, such as deeper motivations for using AI tools and the role of educational institutions, were explored in limited depth. This limitation requires further research.

Our research provides only a snapshot, but a longitudinal study could help to explore how students' attitudes and usage patterns towards AI evolve as their studies progress, and what factors influence the long-term integration of technology into their learning processes. Since the research focused on the humanities, social sciences, and teacher education, it is worth further exploring the extent to which AI can be integrated into these courses and what pedagogical strategies can help these students to successfully use AI. The results of the research showed hat access to AI is not equal for all groups of students. Further research is needed to explore what institutional support can help integrate AI tools into higher education ethically and inclusively.

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