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Article

Artificial Intelligence in Stem Programs to Develop Human Capital

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Abstract: This study analyzes the use of artificial intelligence (AI) tools by students at the Technical University of Madrid (Spain) in science and engineering disciplines, based on a survey of 94 participants. The objective was to identify usage patterns and their relationships with variables such as academic performance, perceived learning, ethics, trust, knowledge, and recommendation. Descriptive statistics and association tests (e.g., chi-square, the Phi, and Cramér's V) were used to assess the strength of the relationships between categorical variables. The results show that most students have used AI tools for academic purposes and report a positive perception in terms of learning and knowledge. Significant associations were found between AI use and learning-related variables, while others like academic performance and trust did not show statistical significance. Minor gender-based differences were observed, but not statistically significant. These findings suggest a growing normalization of AI use in technical education, where perceptions of usefulness and ethics outweigh the impact on academic performance. The implications are discussed within the framework of designing pedagogical strategies for the responsible integration of AI in higher education.

Keywords: Artificial Intelligence, University Students, STEM, Academic Use of AI, Ethics in Education, Self-Regulated Learning

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1. Introduction

Artificial intelligence (AI) has rapidly evolved into a transformative force reshaping global economic, institutional, and social systems. Defined broadly as the capacity of machines to perform tasks that typically require human intelligence—such as learning, reasoning, and decision-making (Russell & Norvig, 2021)—AI now influences diverse sectors including healthcare, finance, transportation, industry, and public services. Its strategic importance has been emphasized in international frameworks such as the United Nations 2030 Agenda for Sustainable Development, which highlights AI's potential to enhance innovation, education, and institutional effectiveness (UNESCO, 2021).

Recent advances in AI technologies, such as machine learning, natural language processing, and computer vision, have accelerated its adoption across multiple domains (Goodfellow, Bengio, & Courville, 2016). While AI offers promising opportunities for efficiency gains, personalized services, and human development (Brynjolfsson & McAfee, 2014), it also raises complex questions about labor displacement, ethical boundaries, and social inequities (Crawford & Calo, 2016; Mittelstadt et al., 2016). Scholars argue that AI should be understood not merely as a technological innovation but as a socio-technical phenomenon embedded in cultural, economic, and political contexts, which both shapes and is shaped by human values and institutional frameworks (Eubanks, 2018; Bender et al., 2021).

Despite its broad promise, AI adoption remains uneven, particularly in developing and emerging economies, where infrastructural limitations, unequal digital literacy, and insufficient regulatory frameworks constrain its full potential (ITU, 2022; OECD, 2021). In addition, concerns about data privacy, algorithmic bias, and ethical governance continue to provoke global debates, underscoring the need for inclusive and context-sensitive approaches to AI development and deployment (Floridi et al., 2018).

Within this broader landscape, the academic sector has emerged as both a testing ground and a contested space for AI integration. Universities increasingly adopt AI-powered tools for administrative tasks, research assistance, and - more controversially- teaching and learning. While AI offers possibilities for personalized learning, adaptive systems, and the development of 21st-century skills, its educational deployment raises pedagogical, ethical, and epistemological questions. These include the role of human agency in learning, concerns about academic integrity, and the preparedness of educators and institutions to support critical and reflective use of AI (Luckin et al., 2016; Vieriu & Petrea, 2025).

This study seeks to analyze how students at the Technical University of Madrid (UPM) engage with AI, offering a comprehensive overview of its usage and implications within the academic context. Findings suggest that AI is not only altering how students approach academic tasks, but also reshaping their perceptions of learning and performance. In light of these changes, promoting critical digital literacy among students and educators becomes increasingly important to ensure the responsible, ethical, and effective use of AI in higher education.

To explore these dynamics, a survey was conducted addressing several key factors related to AI use, including students' prior knowledge, trust in AI tools, ethical concerns, academic performance, and the learning process. Descriptive and correlational statistical analyses provided a nuanced understanding of how students perceive and integrate AI into their academic routines. A total of 92 students participated, with demographic and academic variables examined in relation to AI usage.

Literature Review and Hypothesis Formulation

Artificial intelligence (AI) has become a transformative tool in education, enabling personalized learning, enabling personalized learning, automating processes, and fostering the development of key 21st-century competencies (Zepeda Hurtado et al., 2024). Furthermore, it has been noted that the integration of AI can help reduce educational gaps if implemented with criteria of equity and accessibility. In this regard, Atencio-Gonzáles (2023) emphasizes that AI should not only be seen as a technical tool but as an agent of change that requires critical reflection on its impact on educational equity and quality. For example, AI-powered platforms such as adaptive learning systems have been shown to enhance student engagement and performance by providing real-time feedback and tailored learning pathways (Luckin et al., 2016). However, the implementation of AI in education presents challenges, particularly around teacher training and the ethical implications of its use.

Its integration into academic settings has prompted research seeking to understand the factors influencing its adoption and use by students. In addition to traditional demographic variables, recent literature explores psychological, cultural, and contextual factors that shape students' perception and behaviour toward artificial intelligence. Obenza et al. (2023) highlight, for example, that familiarity with previous digital tools and exposure to innovative technological environments positively correlate with more open attitudes toward using AI in academic tasks. Likewise, the degree of student autonomy and their self-regulated learning orientation also influence their willingness to integrate these tools into their learning routine. These dimensions open new lines of research that go beyond a purely instrumental approach, allowing for an understanding of AI adoption as a multifactorial process where institutional culture, prior experiences, and personal attitudes are intricately intertwined.

One of the most relevant approaches in recent literature is the analysis of personal and contextual variables that affect the perception and use of AI. This study presents the analysis of the following personal variables: gender, area of study, prior knowledge about AI, formal training in AI, ethical perception, level of trust, emotional attitude, and affective evaluation toward AI. Regarding contextual variables, notable ones include faculty integration of AI, warnings or prohibitions from faculty, perceived impact on academic performance, perceived benefit in learning, and future recommendation of use to third parties. Each of these will be explained and argued next, according to the reviewed literature.

Regarding gender and area of study, according to studies such as González González (2023), engineering students tend to show a greater intention to use and positive evaluation of AI compared to social science students, due to their greater exposure to emerging technologies. However, studies show that gender differences in the adoption and perception of these technologies tend to be minimal or non-significant in contexts where access and training are equitable (Maxwell et al., 2025). Along these lines, this paper presents the first four hypotheses to be tested:

H_1: Area of study (science vs. engineering) significantly influences the use of AI tools.

H_2: Gender does not significantly influence the greater use of AI.

The level of prior knowledge about AI is also a determining factor. Students with intermediate or advanced knowledge tend to perceive AI as more suitable and beneficial, which translates into a greater perceived integration into their learning processes. As Rivera-Novoa and Duarte Arias (2025) point out, students with greater familiarity and prior experience with artificial intelligence tools tend to integrate them more actively and significantly into their learning processes, perceiving them as complementary resources that enhance their cognitive abilities. This perception is reinforced by previous positive experiences and clarity about the benefits that AI can provide, such as content personalization or immediate feedback. For this reason, we formulate the following hypothesis for this work:

H_3: Students who have knowledge and training in artificial intelligence show a higher frequency of use.

Likewise, the emotional evaluation toward AI — that is, whether it is perceived positively, negatively, or neutrally — directly influences the intention to use it. Students who positively evaluate AI tend to consider it a tool that greatly benefits their learning, while those with negative perceptions may see it as a threat or a source of dehumanization of the educational process (Zepeda Hurtado et al., 2024). On the other hand, the incorporation of artificial intelligence in academic contexts has generated ethical and institutional tensions, especially regarding authorship, originality of knowledge, and the appropriate use of generative tools. Else (2023) and Stokel-Walker (2023) have warned that the indistinction between human-generated and AI-generated content can affect academic integrity and the very meaning of the educational process. Added to this is the need for institutions to define clear regulatory frameworks that establish not only limits but also training opportunities in the ethical and critical use of these tools. In this way, the institutional and normative context emerges as a factor that influences students' perceptions, attitudes, and decisions. Therefore, the following hypotheses are formulated:

H_4: Ethical perception regarding the use of AI in academia is associated with greater use and a greater recommendation of its use to other students.

H_5: The higher the level of confidence in the use of AI tools, the greater the frequency of use by students.

The perceived impact on academic performance and the degree of AI integration into their learning process are also key variables, as they help develop critical thinking and autonomy. Mejía and Sargent (2023) highlight that tools like ChatGPT allow students to generate hypotheses, contrast arguments, formulate complex questions, and structure answers with greater clarity, contributing to the development of critical thinking and higher-order cognitive skills. However, they emphasize that these benefits depend on guided and reflective use within pedagogical environments that promote autonomy and critical evaluation. These practices, while requiring appropriate pedagogical guidance, open new possibilities for rethinking traditional teaching methods, orienting them toward more active and reflective models. Thus, AI is conceived not only as a complementary resource but as a catalyst for active, student-centered methodologies. According to other recent studies, when students perceive that AI is fully integrated into their educational environment and significantly benefits their learning, their willingness to use it increases considerably (González-González, 2023). Conversely, partial or poorly communicated integration can generate uncertainty or rejection. In line with this work, the following hypothesis is formulated:

H_6: Students who perceive a greater positive impact of AI on their academic performance tend to use and recommend AI more.

H_7: Students who perceive that AI benefits their learning process use it more frequently and recommend it.

In relation to faculty, their attitude toward the use of AI tools in the classroom can significantly influence students' adoption of these technologies. Studies show that explicit warnings or prohibitions regarding AI use—especially in assessment contexts—may create a climate of distrust or fear that limits its use even in legitimate formative activities (Rodríguez Garcés et al., 2024). This dynamic is reinforced by the lack of clear institutional policies, leaving the acceptance or rejection of these tools to the discretion of the teacher, generating uncertainty among students (López and Hernández, 2023).

Crompton and Burke (2023) point out that many teachers lack the necessary training to integrate these technologies into their practices, which limits their impact and creates inequalities in implementation. Consequently, simply making tools available is not enough: an institutional training strategy is required, including digital literacy and critical pedagogy programs for AI use, thus ensuring a significant appropriation of these technologies in the classroom.

On the other hand, when teachers actively integrate AI into their pedagogical practices, for example, through automated feedback, intelligent tutoring systems, or virtual assistants, students tend to normalize its use and perceive it as a legitimate part of the learning process. This integration not only acts as a model for responsible use but also reduces uncertainty and fear associated with possible sanctions or ethical misunderstandings (Kroff et al., 2024). Studies like Akgun and Greenhow (2022) also indicate that explicit warnings or prohibitions regarding AI use [...] can create a climate of distrust or fear that limits its use even in legitimate formative activities. Based on these variables, two hypotheses have been defined:

H_8: Students who perceive greater integration of artificial intelligence by faculty in the classroom tend to use it more frequently in their academic activities.

H_9: The existence of explicit warnings or prohibitions by faculty regarding the use of AI tools is associated with a lower frequency of use of these tools by students.

Finally, a last control hypothesis is detailed:

H_{10}: There is a positive and significant relationship between the frequency of AI use and the recommendation of its use to third parties.

Theoretical Framework

Models like the Technology Acceptance Model (TAM) and its extensions have been used to explain how perceived usefulness, ease of use, and emotional attitudes determine the adoption of emerging technologies in educational contexts. Introduced by Davis et al. (1989), TAM has a solid foundation in the theory of reasoned action, asserting that the actual use of a system depends on an individual's behavioral intention. This intention, in turn, is influenced by the attitude toward use and perceived usefulness.

The Perceived Usefulness (PU) component assesses the extent to which a person believes that using a technology will enhance their job performance and enable them to achieve better results (Agbaglo & Author, 2022; Davis, 1989; Scherer et al., 2019). On the other hand, the Perceived Ease of Use (PEOU) component measures the perceived effort an individual experiences when using that technology (Davis et al., 1989). According to TAM, PU and PEOU jointly influence the intention to use a specific technology, underscoring that the desire to use a technology precedes its actual use (Agbaglo & Bonsu, 2022).

By applying the TAM model, researchers can anticipate users' willingness to adopt a technology based on their perceptions. In fact, a recent study adapted TAM to the Spanish context and applied it to university students, confirming its structural validity and its ability to explain the intention to use digital technologies in virtual learning environments (Bolaño-García, 2024). In parallel, a systematic review of AI implementation in schools between 2019 and 2023 identified that this technology has high potential to transform teaching, improve educational management, and personalize learning, provided it is implemented with ethical planning and adequate teacher training (Flores-Vivar and García-Peñalvo, 2023). This evidence suggests that TAM can be a key tool to guide the effective and responsible integration of AI in education.

It should also be noted that some authors propose complementary models that incorporate social, cultural, and emotional dimensions. For example, the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) model expands on TAM's focus by including factors such as social influence, habit, hedonic motivation, and facilitating conditions (Venkatesh et al., 2012). Its application in educational contexts could offer a more comprehensive view of user intention and experience, especially concerning emerging tools like generative AI, whose use involves not only functional aspects but also emotional, ethical, and social perceptions.

2. Materials and Methods

Sample and Data collection

Data were collected through a digital questionnaire created using Google Forms, which was distributed via a link posted on the Moodle platform, the learning management system used by the Technical University of Madrid. The link was shared across various courses in science and engineering degree programs, allowing access to active university students within the target population.

The questionnaire consists of 17 questions, covering aspects related to knowledge, use, perception, trust, training, and ethical considerations regarding artificial intelligence tools, as well as sociodemographic and academic variables (such as gender and perceived academic performance). The full structure of the questionnaire is provided in the Appendix at the end of the article.

The final sample included 92 students. From a statistical perspective, the target population is considered very large, as it comprises over 100,000 university students enrolled in various degree programs at the Technical University of Madrid. Therefore, and due to the exploratory nature of the study, a non-probability purposive sampling method was used, taking advantage of institutional access to the Moodle platform.

Table 1. Technical data of the analysis.

Population	
Unit	Science and Engineering Students of Technical University of Madrid.
Questionnaire design	Self-developed using the Google Forms tool
Population types	More than 100,000 elements.
Time period	Data from 2025
Sampling	
Type of sampling	Non-probability purposive sampling method
Sample size	94 Science and Engineering Students Technical University of Madrid.
Sampling error (approx.)	0.028 (p=q=0.50).
Level of confidence	95% (K=2 sigma).
Data treatment	Statistical Package for the Social Sciences (SPSS)

Source: author-compiled data.

Variables and Measures

Tables 2 and 3 are analysed the different variables that will be analysed:

Table 2. Nominal and categorical variables definition.

Variable	Abbreviation	Type of Measurement	Values	Hypotheses
Use AI	USE	Ordinal categorical	4= Always 3= Frequently 2= Sometimes 1= Rarely 0= Never	H_1, H_2 H_3, H_4, H_5, H_6, H_7, H_9.
Gender	GEN	Nominal categorical	0 = male 1 = female	H_2
Type of Degree Program	PROGRAM	Nominal categorical	0=science 1=engineering	H_1, H_2
Confidence level	CONFIDENCE	Ordinal categorical	3 = high 2 = moderate 1 = low	H_5
Prior knowledge about AI before entering university	KNOWKEDGE	Ordinal categorical	1 = none 2 = basic 3 = intermediate	H_3
Formal training received on AI	TRAINING	Nominal categorical	1=syes0=no	H_3
Ethical opinion on AI use in academia	ETHICAL	Ordinal categorical	5 = completely adequate 4 = somewhat adequat 3 = neutral / indifferen 2 = somewhat inadequate 1 = completely inadequate	H_4
Teacher's warning or prohibition on AI use	PROHIBITION	Nominal categorical	1=yes 0=no	H_9
Perceived impact of AI use on academic performance	PERFORMANCE	Ordinal categorical	5 = very positively 4 = positively 3 = neutral / indifferen 2 = negatively 1 = very negatively	H6
Perceived influence of AI use on learning process	LEARNING	Ordinal categorical	5 = greatly benefits 4 = somewhat benefits 3 = neutral / indifferen 2 = somewhat harms 1 = greatly harms	H_7
Perception of AI integration by professors	INTEGRATION	Ordinal categorical	0 = don't know 1 = not integrated at al 2 = somewhat	H_8

Recommendation of AI use to other students	RECOMMENDATION	Ordinal categorical	integrated 3 = fairly integrated 4 = fully integrated 5 = Definitely yes 4 = Probably yes 3 = Don't know / Not sure 2 = Probably not 1 = Definitely not	H_4, H_6, H_7 y H_{10}

Source: author-compiled data

Table 3. Multiple-response variables.

Variable	Abbreviation
Areas of AI use in academic work	Areas
Types of AI tools used	Tools
Reasons for using AI	Reasons

Source: author-compiled data

Analysis methodology

The analysis was carried out in several stages. In the first phase, a descriptive quantitative analysis was conducted. Basic statistical techniques such as minimums, maximums, means, and standard deviations were applied to characterize the sample and summarize the distribution of responses across key variables. These descriptive results provided a general overview of the students' profiles and their interaction with artificial intelligence (AI) tools in academic settings.

Subsequently, a correlation analysis was performed to explore the relationships between variables such as AI usage, perceived learning, academic performance, ethical concerns, and trust in these technologies. For categorical variables, Chi-square tests of independence were conducted, and the strength of association was assessed using the Phi coefficient and Cramér's V, depending on the dimensions of the contingency tables.

Given the nature of the sample and the type of variables analysed, no parametric assumptions were required. The analyses were carried out using statistical software tools suitable for social science research (e.g., SPSS or equivalent). Statistical significance was set at $p < 0.05$, although values below 0.10 were also considered indicative of potential trends worth discussing in exploratory studies.

In a second stage, a specific frequency analysis was conducted for the multiple-response questions, to identify usage patterns and preferences regarding the areas of application and types of AI tools used by students.

The combination of both analytical approaches provided a comprehensive view of the phenomenon under study, facilitating the identification of general trends, significant associations, and potential future lines of research regarding the academic use of artificial intelligence.

3. Results and Discussion

The results of the descriptive statistics and correlations are shown in tables 4-5 and the frequencies (multiple-response questions) in Figures 1-3.

Table 4. Descriptive Statistics.

Variable	N	Min.	Max	Mean	Std. Dev.
USE	94	1	4	3.10	0.835
GEN	92	0	1	0.71	0.455
PROGRAM	89	0	1	0.66	0.475
CONFIDENCE	94	1	3	2.10	0.550
KNOWLEDGE	94	1	3	1.72	0.709
TRAINING	93	0	1	0.16	0.370
ETHICAL	94	0	5	3.44	1.053
PROHIBITION	94	0	1	0.71	0.455
PERFORMANCE	94	2	5	3.74	0.829
LEARNING	94	2	5	3.83	0.912
INTEGRATION	94	0	3	0.97	0.754
RECOMMENDATION	94	2	5	4.20	0.770

Source: author-compiled data

Regarding the results of the descriptive analysis, it's worth highlighting that the mean usage (USE) is 3.10 out of 4. This indicates frequent use of AI by students and supports the general hypothesis of normalized use in STEM contexts.

It's also important to note the mean for confidence (CONFIDENCE) with AI, which is 2.10. This suggests moderate confidence, consistent with the values obtained for ethical perception (ETHICAL) at 3.44 and recommendation (RECOMMENDATION) at 4.20.

As for students' prior knowledge (KNOWLEDGE), the mean is 1.72, indicating that most have only basic or intermediate knowledge. It's striking that, despite this limited knowledge, the frequency of AI use is high.

Finally, concerning faculty integration (INTEGRATION), the mean drops to 0.97 out of 4. This points to still limited integration by professors, as noted in studies by Kroff et al. (2024) and Crompton & Burke (2023).

Table 5. Chi Square.

Cross-tabulation	χ^2 (Chi-Square)	df	p-value	Hypotheses
USE × PROGRAM	5.39	3	0.145	H_1
USE × GEN	0.62	3	0.892	**H_2**
USE × CONFIDENCE	16.196	6	0.013	**H_5**
USE × KNOWLEDGE	1.388	6	0.967	H_3
USE × TRAINING	3.202	3	0.362	H_3
USE × ETHICAL	34.39	15	0.003	**H_4**
USE × PROHIBITION	2.749	3	0.432	H_9
USE × PERFORMANCE	20.967	9	0.013	**H_6**
USE × LEARNING	32.385	9	<.001	**H_7**
USE × INTEGRATION	10.363	9	0.322	H_8
USE × RECOMMENDATION	53.271	9	0.001	**H_{10}**
RECOMMENDATION x PERFORMANCE	34.042	9	<.001	**H_6**
RECOMMENDATION × ETHICAL	44.639	15	<.001	**H_4**
RECOMMENDATION x LEARNING	47.897	9	<.001	**H_7**

Source: author-compiled data. The hypotheses that are accepted are highlighted in bold.

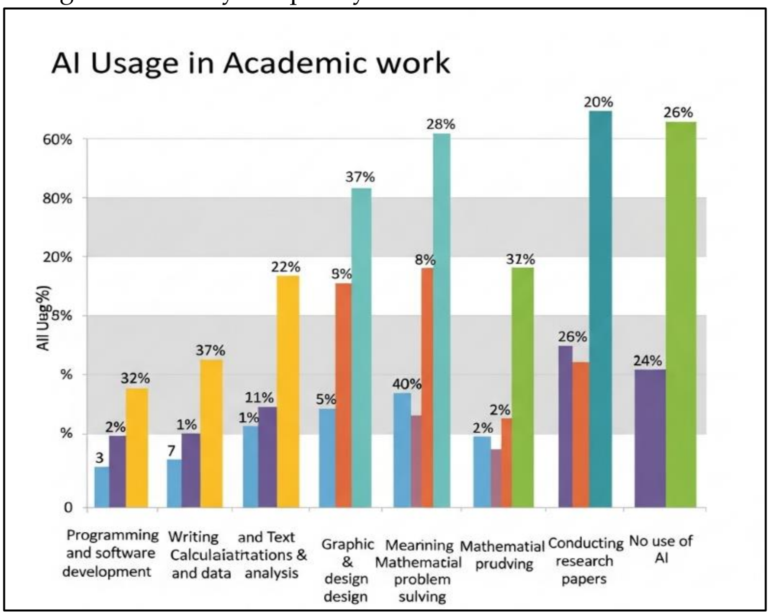
The results of the chi-square analysis reveal several statistically significant associations between the use of artificial intelligence tools (USE) and variables related to students' perceptions and experiences.

First, a significant relationship was found between AI use and the level of confidence reported by students (USE × CONFIDENCE, p = 0.013), supporting hypothesis H_5: the greater the confidence, the higher the frequency of the use. Davis et al. (1989) already reported similar findings in their work applying the TAM model, highlighting that confidence influences the intention to use emerging technologies. Likewise, the ethical perception of AI use showed a significant association with its use (USE × ETHICAL, $p = 0.003$), supporting hypothesis H_4, which states that a positive ethical evaluation favours the adoption of these technologies. This latter result aligns with Flores-Vivar & García-Peñalvo (2023), who emphasize the importance of ethics in the responsible integration of AI in educational contexts.

A significant relationship was also observed between AI use and the perception of its impact on academic performance (USE × PERFORMANCE, $p = 0.013$), supporting hypothesis H_6. This suggests that students who perceive benefits in their academic performance tend to use AI more frequently (Mejía & Sargent, 2023). Hypotheses H_7 and H_{10} are also supported, as a statistically significant association was found between the perception that AI benefits the learning process and both its use ($p = 0.013$) and its recommendation to other students ($p < 0.001$), reinforcing the idea that perceived usefulness in learning drives the adoption and dissemination of these tools. Bolaño-García (2024) also highlights in his work that a positive perception of AI's usefulness drives both its use and its diffusion among others.

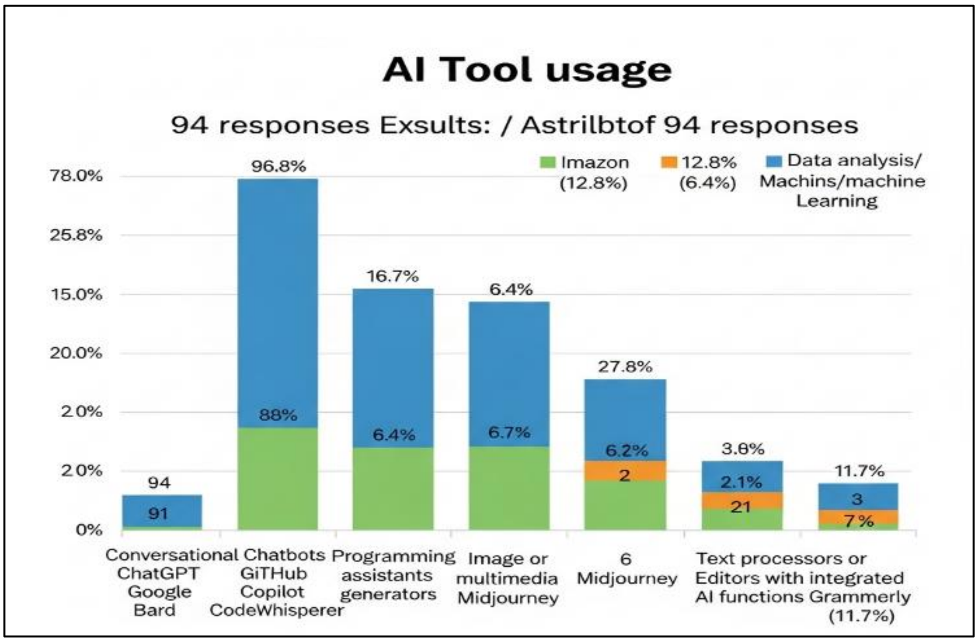
On the other hand, no significant associations were found between AI use and variables such as gender (USE × GEN, $p = 0.892$), in line with studies such as Maxwell et al. (2025), or field of study (USE × PROGRAM, $p = 0.145$), confirming that these sociodemographic characteristics do not significantly influence AI adoption.supporting hypothesis H_2 and not supporting H_1. Similarly, variables related to formal training (USE × TRAINING) and prior knowledge (USE × KNOWLEDGE) did not show statistical significance, partially questioning hypothesis H_3 and suggesting that other factors may play a more significant role in the decision to use AI in academic contexts. However, this result contradicts findings from studies such as Rivera-Novoa and Duarte Arias (2025).

I the present study, hypotheses H_8 and H_9 were not supported by the statistical results obtained. The perception of AI integration by faculty (INTEGRATION, H_8) did not show a significant association with student use ($p = 0.322$), indicating that although faculty integration is limited, it does not appear to directly influence student behavior. Finally, the existence of explicit warnings or prohibitions (PROHIBITION) by faculty (H_9) was also not significantly associated with lower usage frequency ($p = 0.432$), which could be interpreted as a sign that students make decisions about AI use beyond institutional restrictions. These results do not support those of Kroff et al. (2024) and Rodríguez Garcés et al. (2024), but they invite reflection on the complexity of the factors influencing AI adoption in educational contexts and the need to continue exploring variables beyond purely structural or normative ones.



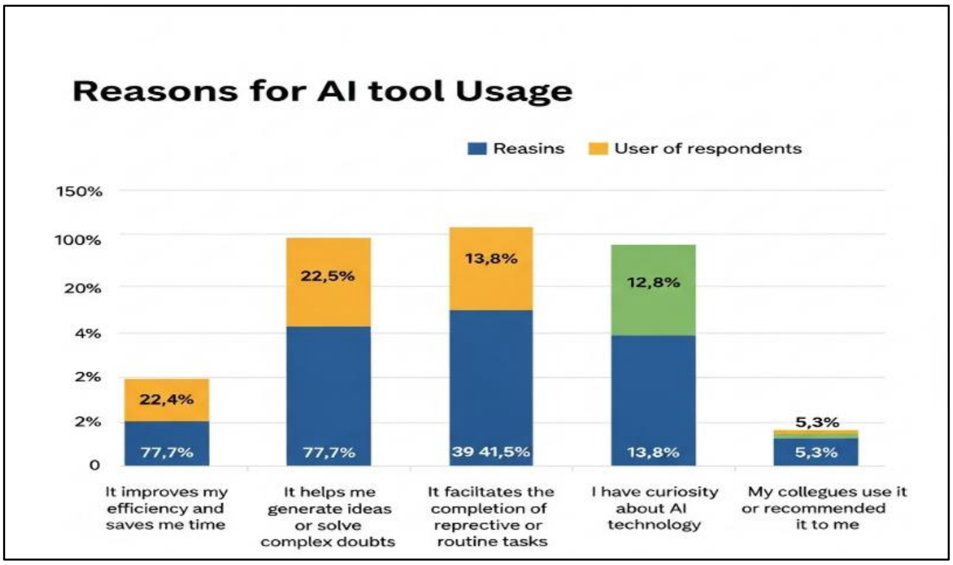
Source: author-compiled data

Figure 1. Frequency Areas of AI application.



Source: author-compiled data

Figure 2. Frequency of Tools Usage.



Source: author-compiled data

Figure 3. Frequency Reasons for using AI.

The results from the figures complement and reinforce the quantitative findings of the study. In Figure 1 (Areas of Application), there is a high concentration of artificial intelligence use of AI tools in tasks related to writing, information retrieval, and content synthesis. This trend which is consistent with the perceived usefulness for self-regulated learning, as these activities allow students to organize and deepen their understanding of content autonomously. This finding is consistent with Zepeda Hurtado et al. (2024), who highlight how AI can foster autonomous learning and educational personalization. In Figure 2 (Tools Used), applications such as ChatGPT and Grammarly stand out, suggesting that generative and text-correction tools lead technological adoption in academic settings, in line with studies such as Obenza et al. (2023).

Finally, Figure 3 (Reasons for Use) reveals that the main motivations for using AI "are "saves time," "improves work quality," and "helps better understand the content."" These responses align with the perceived usefulness component of the TAM model, reinforcing the idea that the adoption of these technologies is strongly driven by practical and tangible benefits in the learning process. This is consistent with the work of Davis et al. (1989) and Scherer et al. (2019), who explain that perceived usefulness is a key predictor in the adoption of educational technologies.

4. Conclusions

This study confirms the growing normalization of artificial intelligence (AI) use of AI tolos among STEM students at the Polytechnic University of Madrid. The majority of participants report frequent use of these technologies, particularly for writing tasks, retrieving information, and synthesizing content. The significant correlations between AI use and variables such as confidence, ethical perception, academic performance impact, and perceived learning benefits reinforce the applicability of models like TAM in educational contexts.

Hypotheses H_2, H_4, H_5, H_6, H_7, and H_{10} are supported, indicating that positive perceptions of ethics, confidence in use, and perceived benefits in learning and academic performance are key factors in the adoption and recommendation of these tools. In contrast, hypotheses H1, H3, H8, and H9 were not supported, suggesting that neither sociodemographic characteristics nor faculty actions (integration or prohibition) have a direct impact on usage frequency, at least within this sample. The lack of significant associations for H1 and H3 may suggest that sociodemographic and training-related factors are less influential than attitudinal or perceptual variables in AI adoption.

Based on the findings, it is recommended to promote critical digital literacy among both students and faculty, to establish clear institutional policies regarding AI use, and to integrate AI through critically informed pedagogical strategies. These findings reinforce the relevance of TAM-based strategies, emphasizing the importance of perceived usefulness and ease of use in promoting AI adoption. Additionally, it is suggested to leverage the potential of these tools to strengthen autonomous learning and critical thinking, and to incorporate ethical training modules that address responsible AI use, authorship, and academic integrity, given the significant role of ethical perception in AI adoption, as well as to expand future research to other disciplines and educational contexts to validate and enrich the findings.

This study presents some limitations that should be considered. First, the sample size is small and limited to a single institution and students from scientific and technological fields, which may limit the generalizability of the findings. Moreover, the use of non-probabilistic sampling, the self-reported nature of the data may introduce self-report bias. Finally, although multiple variables were analysed, factors such as socioeconomic status, teaching experience, or course type were not included, which could influence AI use in academic contexts. Overall, this study contributes to a growing body of evidence on the pedagogical integration of AI in higher education, offering insights for both policy and practice.

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