NEYART
Magazine
ISSN: 2992 - 7161

GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS IN HIGHER EDUCATION STUDENTS

GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS IN HIGHER EDUCATION STUDENTS

Pizarro Gurrola Rubén
National Technological Institute of Mexico/I. T. of Durango https://orcid.org/0009-0004-2618-0166
rpizarro@itdurango.edu.mx

Moorillón Soto Ana Louisa
National Technological Institute of Mexico/I. T. de Durango https://orcid.org/0009-0009-5030-6124
amoorillon@itdurango.edu.mx

Domínguez Flores Araceli Soledad
National Technological Institute of Mexico/I. T. of Durango https://orcid.org/0009-0009-9349-3249
adominguez@itdurango.edu.mx

Calzada Terrones Jeorgina
National Technological Institute of Mexico/I. T. of Durango https://orcid.org/0009-0002-1040-233X
jcalzada@itdurango.edu.mx

Rodríguez Rivas José Gabriel
National Technological Institute of Mexico/I. T. of Durango https://orcid.org/0000-0002-7031-5097
gabriel.rodriguez@itdurango.edu.mx

DOI: https://doi.org/10.61273/neyart.v1i2.90 | **Received:** January 15, 2025 | **Accepted:** March 20, 2025 | **Published:** April 15, 2025

Abstract: This article evaluates the use of generative artificial intelligence (GAI) tools among higher education students at the Durango Institute of Technology. A *Likert* scale survey was administered to a sample of *452* students using an instrument with a *Cronbach's* reliability of 0.77. A factorial component analysis was performed using *Kaiser-Meyer-Olkin* and *Bartlett* tests to assess the validity of the instrument. Three dimensions were evaluated: impact and benefit of GAI; familiarity and perception; ethical considerations, privacy, and future aspects. The results highlighted that students did find usefulness and positive impact in their learning and moderate familiarity with the tools, although they showed indifference toward ethical aspects, privacy, and future aspects with the use of GAI. The nonparametric *Kruskal-Wallis* test revealed that there are no significant differences between the professional careers they study regarding the use of these tools. It is recommended that the study be replicated in other institutions to explore broader patterns. The conclusions emphasized that, although IAG improves productivity and learning, it is necessary to promote the ethical and supervised use of these technologies in educational settings.
Keywords: Generative artificial intelligence, learning, use, higher education students.

Abstract: This article evaluates the topic of the use of generative artificial intelligence (GAI) tools in higher education students at the Instituto Tecnológico de Durango. A Likert scale survey was applied to a sample of 452 students using an instrument that had a Cronbach reliability of 0.77. A component factor analysis was applied through Kaiser-Meyer-Olkin and Bartlett tests that assessed the validity of the instrument. Three dimensions were evaluated: impact and benefit of GAI; familiarity and perception; ethical considerations, privacy, and future aspects. The results highlighted that students did find usefulness and a positive impact on their learning and a moderate familiarity with the tools, although they showed indifference towards ethical aspects, privacy, and future aspects with the use of GAI. The nonparametric Kruskal-Wallis test revealed that there are no significant differences between the professional careers they study regarding the use of these tools. It is recommended to replicate the study in other institutions to explore broader patterns. The findings emphasized that while GAI improves productivity and learning, there is a need to promote ethical and supervised use of these technologies in educational settings.
Keywords: Generative artificial intelligence, learning, usage, higher education students.

INTRODUCTION

In recent years, the use of generative artificial intelligence (GAI) has become popular, and individuals, companies, and institutions in general have taken advantage of its benefits. In higher education, the use of GAI tools has enriched and aided student learning.

GAI tools are the product of evolution, the result of academic and research efforts, and are part of artificial intelligence, which involves technology that solves tasks and problems as humans do.

In his article, Corredera (2023) states that AI are methods and applications capable of generating new content, including text, images, software, music, and video with unique characteristics.

Martínez González (2023) mentions that students use IAG in their academic work because it is an easier and faster way to do it, avoiding the fatigue of consulting other sources of information and passing it off as their own work without giving credit to where they obtained the information.

In the results of his research, he argues that students are aware that they use IAG tools inappropriately, simply to complete their assignments without verifying the accuracy of the information in other sources. García Sánchez (2023) mentions that the *ChatGPT* tool *(real-time conversation based on Generative Pre-trained Transformer*) as an IAG tool has had a strong impact on society and within the academic field; it is innovative in the way it promotes learning.

In the results presented by Menacho, Pizarro, Osorio, Osorio, and León (2024), after conducting a survey of a sample of *399* higher education students, they found that students have a positive attitude toward the use of AI with the *ChatGPT* tool in their academic activities, making them more productive, but they also show concern in terms of ethics, inaccurate information, and privacy.

AI tools are very important for autonomous teaching and learning and must be used responsibly and ethically, as the results show that 41.4% of students almost always use AI to complete their academic work more quickly. (Menacho Ángeles, Pizarro Arancibia, Osorio Menacho, Osorio Menacho, & León Pizarro, 2024).

The list of IAG tools for education is growing rapidly. These tools can be used for both teaching and learning and are classified as generators of text, video, images, audio, 3D objects, source code, and tools for detecting AI-generated text, among others. (García Peñalvo, Llorens Largo, & Vidal, 2024).

Alpizar Garrido and Martínez Ruiz (2024) highlight the importance of teachers being present in the classroom to supervise students' activities when they are using IAG tools. It is also important for students to identify when data is false or erroneous in IAG results, as well as to learn how to routinely cite and reference research work to avoid plagiarism and presenting work as their own. The results of their research indicate that using IAG tools develops creative skills compared to traditional teaching methods.

With regard to ethical issues and the responsible use of IAG tools, Angles Canlla and Angles Canlla (2024) propose the urgent need to establish regulations, initiatives, policies, and even institutional oversight committees, in addition to training educators in their assertive use, which will result in the responsible training of students.

In a study conducted in Ecuador in a context applied to nursing students, whose objective was to evaluate attitudes toward the use of *ChatGPT*, four dimensions based on the instrument stand out: perceived usefulness; perceived risks; perceived ease of use; and behavior that drove the use of technology (Rojas Villafuerte, 2024). As a result of this study, Rojas Villafuerte (2024) mentions that a positive attitude favors the development of professional skills, in addition to the fact that social influence drives attitudes toward the perception and willingness to adopt technological innovations. He concludes and highlights that perceived usefulness and ease of use are relevant factors to consider that influence the use of IAG among university students.

On the other hand, in his study, Quijano García (2024) proposes a model to evaluate the impact of the use of text-based AI tools in higher education through four dimensions: (1) Quality in the use of AI, considering the quantity, impact, and satisfaction of the content generated, as well as its contribution to learning and ethics in its management; (2) Time and productivity, analyzing efficiency in the completion of academic work and teachers' perceptions of the use of *prompts*; (3) Reading comprehension and writing, based on teachers' evaluation of work; and (4) Institutional perceptions and regulations, covering the opinions of students and teachers, as well as challenges and internal regulations regarding the integration of IAG.

Of these dimensions proposed by Quijano García (2024), those that are similar to this article stand out and allow for the evaluation of students' use of IAG tools: impact and level of satisfaction; perception of the use of IAG, ethics, and responsibility, which are immersed in the model proposed by Quijano García.

The rationale for writing this article is to find out how higher education students studying engineering at the Durango Institute of Technology use IAG tools in their learning process. The importance lies in understanding, comparing, associating, and reflecting on their use.

This article presents the results of applying an instrument that was answered by a sample of higher education students; it measures three dimensions: (1) the impact and benefit of using IAG tools; (2) familiarity with and perception of the use of IAG; (3) ethical considerations, privacy, and the future of IAG for learning.

From the above, the dependent variable to be measured is identified: the use of GAI tools by students in their learning. It will be evaluated through the three dimensions or factors mentioned above; all these factors are associated with the learning process through the independent variable, the student's access to or exposure to the use of generative artificial intelligence (GAI) tools. The research questions addressed in this article aim to answer and measure the use that higher education students make of GAI tools in their learning through the following questions:

What is the impact and benefit of using GAI tools? What is the familiarity and perception of the use of GAI tools? How do students perceive the ethical aspects and considerations, data privacy, and the future of GAI? Is there a significant difference in the use of GAI tools among students in different professional careers?

The article aims to fulfill the general objective of evaluating the use of IAG tools through their access or exposure among students at the Durango Institute of Technology. Use relates to the impact, usefulness, familiarity, perception, ethical considerations, privacy, and future of artificial intelligence for learning as perceived by students when using AIL tools in their learning process.

Comprehensively, the following specific objectives are intended to be achieved:

- Measure the reliability and validity of the instrument and the data collected.
- Describe the impact and benefits of using AIL tools.
- Describe familiarity with and perception of the use of IAG tools.
- Describe students' perceptions of ethical aspects and considerations, data privacy, and the future of IAG.
- Analyze statistical differences among students based on their field of study with regard to the use of IAG tools in their learning.

The hypothesis proposed in this article to answer the question "Is there a significant difference in the use of IAG tools among students in different degree programs?" is as follows: null hypothesis (*Ho*) there are no significant differences between students studying different undergraduate degree programs at the bachelor's degree level with respect to the use of IAG tools; the alternative hypothesis (*Ha*) is that if There are significant differences.

$$Ho: \mu = 0$$

$$Ha: \mu \neq 0$$

DEVELOPMENT

This article is the result of exploratory descriptive research with a transactional and descriptive design (Hernández Sampieri, Fernández Collado, & Baptista Lucio, 2010).

A review of research articles was conducted using keywords such as generative artificial intelligence in higher education, with publication dates from 2023 to the present, mainly on portals such as *Google Academic and Redalyc.*

The instrument was developed with the intention of gathering the opinions of higher education students on the use of generative artificial intelligence tools. The instrument collects data on a *Likert* scale under the following hierarchy: 1: Strongly disagree, 2: Disagree, 3: Indifferent, 4: Agree, and 5: Strongly agree.

Throughout this article, the words dimension, component, and factor are used interchangeably as synonyms with the same meaning; they all refer to aspects that impact the variable to be measured, namely how higher education students use IAG tools in their learning.

Initially, a pilot test was administered to *43* students using a 20-question instrument associated with six dimensions or components: (1) knowledge, familiarity, use, and training with AI tools in school activities; (2) perceived usefulness; (3) specific tools; (4) impact on learning; (5) ethical and privacy considerations; and (6) the future of AI in education.

The pilot test yielded a *Cronbach's* coefficient of *0.889*, which guarantees consistency in the questions and indicates that the instrument is reliable and consistent from acceptable to high (Hernández Sampieri, Fernández Collado, & Baptista Lucio, 2014).

On the other hand, an exploratory factor analysis of the pilot test yielded and suggested three factors instead of six. In agreement with the group of experts (teachers), authors, and co-authors, a strong association was found between questions according to three definitive dimensions: (1) Impact and benefit of using IAG tools; (2) Familiarity and perception of the use of IAG; (3) Ethical considerations, privacy, and the future of IAG for learning.

In the end, the instrument was refined and reduced to 12 questions. The survey was applied to a stratified sample by degree program, with a suggested sample size of $n = 360$ records from a total of *5,692* enrolled students at the Durango Institute of Technology, during the period from August to December 2024, seeking a *95%* reliability with a margin of error of *5%*, according to the following sample size formula:

$$n = \frac{z^2 \cdot N \cdot p \cdot q}{E^2 (N-1) + z^2 \cdot p \cdot q} = 360$$

(Anderson, Sweneey, & Williams, 2008)

The survey was conducted virtually over a two-week period using digital forms created on the *Google Forms* platform. Three strategies were followed: first, a mass email was sent to students' institutional accounts; second, teachers from different degree programs were enlisted to help; and third, degree program coordinators were asked to raise awareness among students and ensure that the required random sample size was achieved.

The survey can be found at the following short link (*URL Uniform Resource Locator*): mailto:https://forms.gle/uzZfH9gS1wrQ2Hfx6; the survey data is available at the link : raw.githubusercontent.com/rpizarrog/analitica_de_datos/refs/heads/main/datos/datos.csv

Table 1 presents the dimensions and respective questions that measure the variable use of IAG tools in learning among higher education students.

Table 1. *Dimension: questions to measure the use of IAG tools for learning in higher education students.*

Dimension/Factor	Questions (*items*)
Impact and benefit of using IAG tools for learning;	1. The use of IAG tools helps my learning and understand the topics studied in my classes 2. IAG tools make it easier for me to complete academic tasks academic tasks 3. IAG tools have helped me improve my academic performance 4. Using IAG gives me a competitive advantage in my professional training professional
Familiarity a nd perception of the use of IAG for learning	5. I am familiar with the use of AI tools. 6. I frequently use IAG tools in my academic activities academic activities. 7. IAG tools are easy to use and understand 8. Learning and the ability to use IAG tools has been autonomous and self-taught.
Ethical considerations, privacy and	9. I believe that the use of IAG tools in the educational field educational field poses ethical risks 10. I am concerned about data privacy (personal and results) when using IAG tools

future of IAG for learning	11. I believe that IAG could replace teachers or change the way we learn in the future 12. Rules and regulations should be established for the use of IAG in education

Source: Own work (2024).

With the data collected, *Cronbach's* reliability coefficient was determined again to ensure that the instrument has acceptable internal consistency (Hernández Sampieri, Fernández Collado, & Baptista Lucio, 2014).

The *Kaiser-Meyer-Olkin (KMO)* test was applied to calculate both the overall index and the individual values of each question in the data set. This test allows the suitability of the data for factor analysis to be evaluated, helping to ensure the validity of the instrument. (Kaiser, 1974).

$$KMO = \frac{\Sigma\Sigma r^2_{ij}}{\Sigma\Sigma r^2_{ij} + \Sigma\Sigma q^2_{ij}}$$

- r^2_{ij} is the square of the correlation between variables *i* and *j*.
- r^2_{ij} is the square of the partial correlation between variables *i* and *j*

The numerator $\Sigma\Sigma r^2_{ij}$ is the sum of the squares of the simple correlations between the variables; the denominator $\Sigma\Sigma r^2_{ij} + \Sigma\Sigma q^2_{ij}$ is the sum of the squares of the simple and partial correlations (Kaiser, 1974). In *R* programming language, the test was performed using the *KMO(cor(data))* function.

Another technique applied to the data collected from the survey was *Bartlett's* test, which is a statistical test used to verify whether there is sufficient correlation between the variables in a data set and to justify factor analysis (Pérez & Medrano, 2010) and (Bartlett, 1950).

Finding that both tests were favorable, confirmatory factor analysis (CFA) was applied with three factors or components that measure the study variable.

Once the reliability and validity of the instrument had been estimated, a descriptive analysis of the data was performed to support the answers to the research questions. Frequency visualization was used with stacked bar charts by question and by dimension, as well as box plots to observe the distribution of the data also by question and by dimension.

To compare means in order to accept or reject the stated hypothesis that there is no difference in usage between students studying different degree programs, normality tests were first performed on all questions.

The *Shapiro-Wilk* test was applied using the *shapiro.test()* function in the *R* programming language. To apply the *Kolmogorov-Smirnov* test, the ks.test() function, also from *R*, was used. Finally, to apply the *Anderson-Darling* test, the *ad.test()* function from the *nortest* package, also from *R*, was used.

All these tests allow the normality of the data to be evaluated by calculating the *p-value* statistic of interest, which serves precisely to accept or reject the null hypothesis of data normality. If this value is below *0.05*, i.e., at a *95%* confidence level, then the data does not behave normally.

Upon finding that the data did not come from a normal distribution, the nonparametric *Kruskal-Wallis* test, equivalent to the ANOVA test, was used to evaluate whether there were significant differences between students by degree program (Hollander, Wolfe, & Chicken, 2013). To support this test, the data were visualized using a box plot and the significant differences between the factors by degree program were evaluated.

The tool used to perform the corresponding analyses was the R programming language and its *R Studio* work environment in the *Posit Cloud* (2024) with a user account created in advance. https://posit.cloud/content/yours?sort=name_asc

DISCUSSION AND ANALYSIS OF RESULTS

The sample size of *452* was above the suggested sample size of *360*. This data was not biased and did not affect the quality of the analyses performed (Leslie, 1965).

According to information provided by official sources at the Durango Institute of Technology, Table 2 shows the number of students enrolled, the percentage of the sample, the number of students that the stratified sample indicates should have responded in order to meet the sample size, and the number of students who responded to the survey for each degree program.

Table 2. Stratified sample of students by degree program.

Major	Enrolled	Sample %	Number Stratum	Responses
Architecture	918	16.13	58	54
Civil Engineering	632	11.10	40	71
Industrial Engineering	601	10.56	38	36
Computer Systems Engineering	555	9.75	35	49
Business Management Engineering	456	8.01	29	21
Bachelor's Degree in Administration	437	7.68	28	50
Mechatronics Engineering	436	7.66	28	32
Chemical Engineering	414	7.27	26	23
Biochemical Engineering	402	7.06	25	33
Electrical Engineering	262	4.60	17	17
Mechanical Engineering	236	4.15	15	11
Electrical Engineering	145	2.55	9	17
Computer Engineering	106	1.86	7	28
Information Technology and Communications Engineering	81	1.42	5	9
Semiconductor Engineering	11	0.19	1	1
Totals	**5692**	**100.00**	**360**	**452**

Source: Own elaboration (2024).

The red color in the fifth column labeled *Resp.* indicates the number of responses per degree program that do not comply with the suggested stratified sample; however, the data did not show bias in the corresponding analyses nor did they detract from the quality of the analyses performed. Furthermore, it was decided to leave it as is so as not to modify the collected data for reasons of professional ethics.

The *Cronbach's* coefficient value was *0.7722*, which means that the instrument has acceptable internal consistency (Hernández Sampieri, Fernández Collado, & Baptista Lucio, 2014).

The overall *KMO* test is high with a value of *0.85* (above *0.6*), meaning that the data and questions *p1* to *p12* that make up the instrument were suitable for applying factor analysis (Kaiser, 1974).

The *p-value* obtained from the *Bartlett* test was *0,* which is well below *0.05*. This is interpreted as meaning that the correlations between the questions are strong enough to justify a factorial analysis.

Table 3 shows the statistics of the tests calculated in R:

Table 3. *Kaiser-Meyer-Olkin* test and *Bartlett* test for factor analysis.

Kaiser-Meyer-Olkin factor adequacy and Bartlett test Call:
KMO(r = cor(data[, 5:16])) *Overall MSA = 0.85 MSA* *for each item =* *p1 p2 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12* *0.89 0.89 0.87 0.90 0.88 0.89 0.86 0.88 0.66 0.69 0.66 0.65* *Bartlett test* *$chisq: [1] 1822.381* *$p.value: [1] 0* *$df: [1] 66*

Source: Own elaboration (2024).

The factorial analysis concludes that the questions are associated with each other and that there are high correlations above *0.5*, especially between items that measure the same dimension or component, with a noticeable discrimination of *items* over other factors (Hernández Sampieri, Fernández Collado, & Baptista Lucio, 2014).

Table 4 shows the correlations of each question with respect to the initially established factors or dimensions, highlighted in shaded background; it confirms that the first four questions are indeed measuring the same component, given their factor loading on the impact and benefit of using IAG tools. From questions 5 to 8, the correlation values affect the factor associated with familiarity and perception of IAG use. Finally, questions 9 to 12 are associated with the factor of ethical considerations, privacy, and the future of IAG for learning. Question 11, which has to do with considering that IAG could replace teachers or change the way we learn in the future, has the least impact on the component; however, it does discriminate between the other two components. All of the above indicates that the instrument is valid, i.e., the questions measure what they are supposed to measure according to the theoretical construct.

Table 4. Correlation values associated with each factor.

	Factors/Dimensions		
Item	**Impact and Benefit**	**Familiarity**	**Ethical considerations, privacy, and future**
p1	0.7038	0.3246	0.0488
p2	0.6601	0.3830	0.0971
p3	0.7846	0.2335	-0.0451
p4	0.6785	0.1889	0.0252
p5	0.2610	0.6559	0.0472
p6	0.4502	0.4708	0.0867
p7	0.2043	0.6999	0.0332
p8	0.3456	0.6861	0.0268
p9	-0.0961	0.1315	0.6955
p10	0.0466	-0.0076	0.5958
p11	0.1221	-0.0108	0.3461
p12	-0.0357	0.0456	0.6158

Source: Own elaboration (2024).

With regard to the research question, what is the impact and benefit of using IAG tools? According to the questions associated with this dimension, an arithmetic mean of *3.9353* and a standard deviation of *0.9861* were obtained, which means that students range from indifference to agreement that there is a benefit and impact from using IAG tools.

To the research question: What is the familiarity and perception of the use of IAG tools? The arithmetic mean was *3.8617* and the standard deviation was *0.9644,* implying that students are between indifference and agreement that they are familiar with and perceive IAG tools.

NEYART
Magazine
ISSN: 2992 - 7161

In response to the research question: How do you perceive the ethical aspects and considerations, data privacy, and the future of IAG? The mean was *3.2201* and the standard deviation was *1.2512, indicating* that students are between indifference and disagreement and agreement with the ethical aspects and data privacy of the use of IAG tools.

Figure 1 shows a high frequency of responses between 3 and 5, i.e., on a scale of indifferent, agree, and strongly agree to the questions in component one, impact and benefit, and component two, familiarity and perception of the use of IAG. This is confirmed by the statistics of the arithmetic means and their standard deviations for each component, which can be interpreted as meaning that students are impacted and benefit from IAG tools, are familiar with them, and are indifferent to the importance of ethics and data privacy.

With regard to component three, ethical considerations and data privacy, there is a high frequency of indifference, which leaves room for further discussion and reflection.

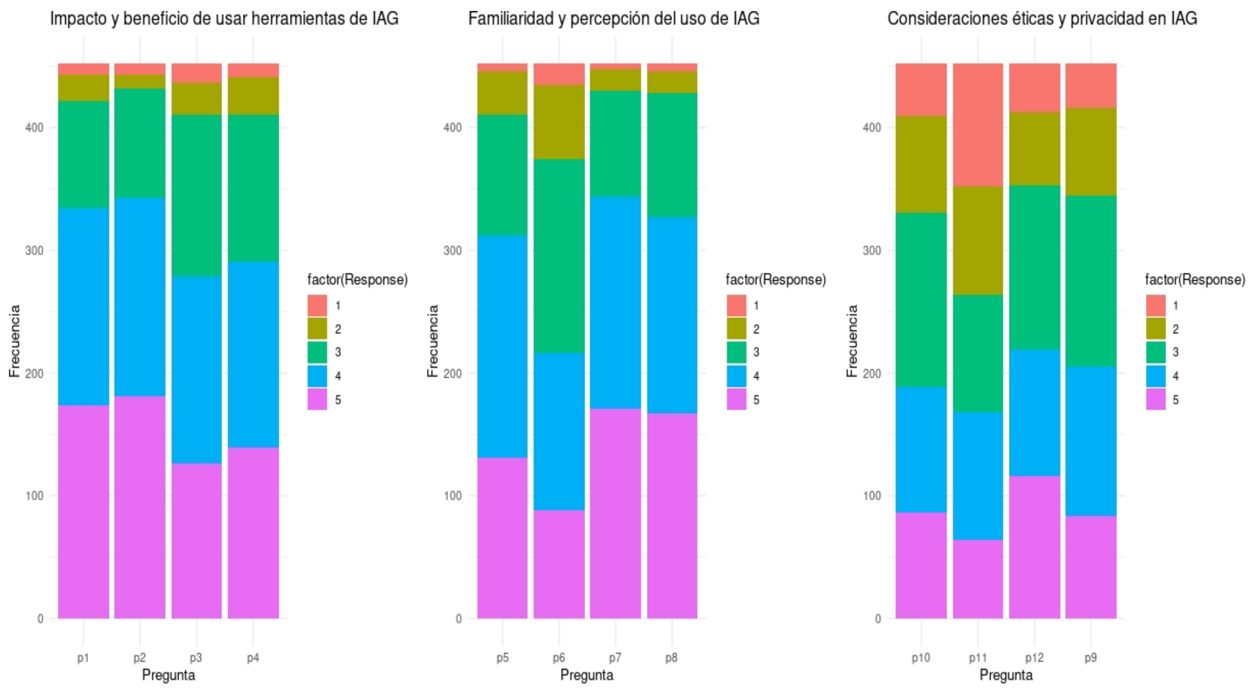

Figure 1. *Frequency of responses by component and questions.*

***Source**: Own elaboration (2024).*

Figure 2 shows the distribution of responses by component and by question; it can be seen that students strongly believe that there is an impact and benefit and are familiar with the use of IAG tools; on the other hand, students are indifferent to ethical issues and data privacy.

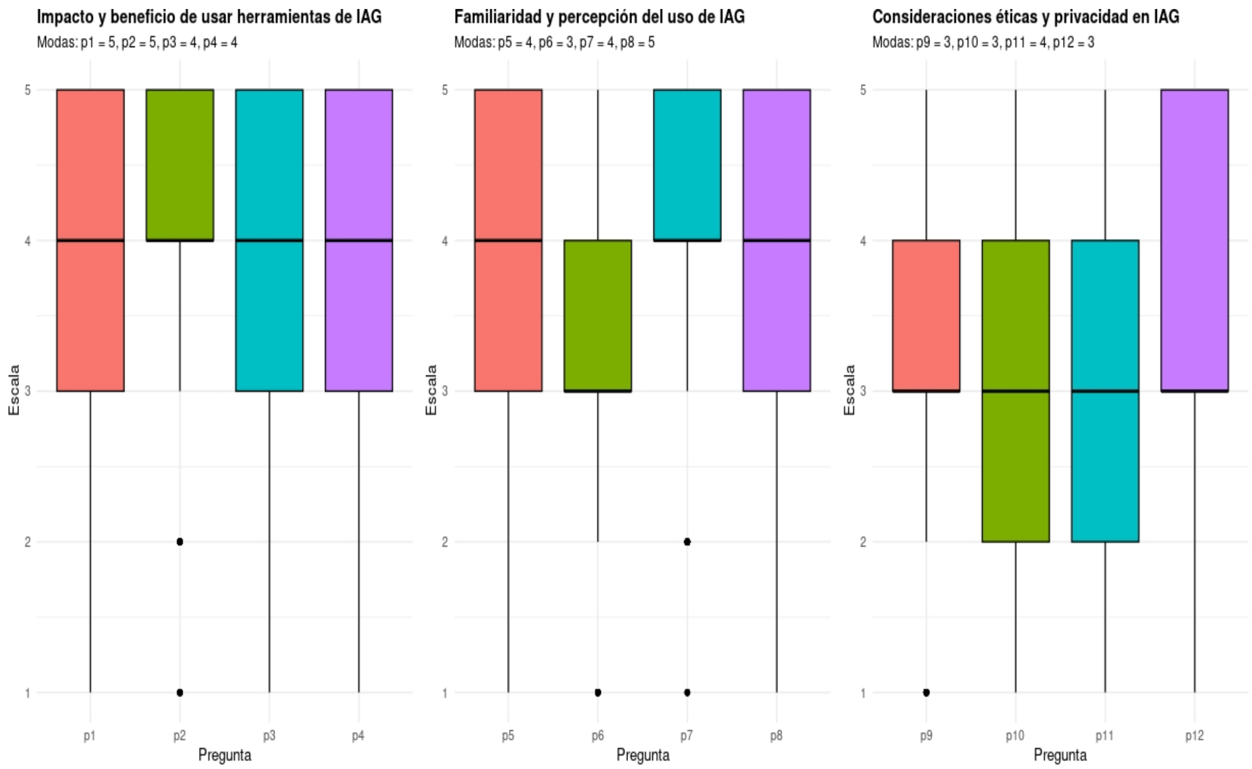

***Figure 2**. Distribution of data by component and by question with modes.*

***Source:** Own elaboration (2024).*

The *p-values* obtained for each question using the *Shapiro-Wilk* test were well below *0.05*, reflecting that the data do not come from a normal distribution.

When performing the *Kolmogorov-Smirnov* test*,* it was found that the *p-values* were also below *0.05*, confirming the non-normality of the data.

When applying the *Anderson-Darling* test*, p-values* below *0.05* were also obtained
, confirming the non-normality of the data.

The *Shapiro-Wilk*, *Kolmogorov-Smirnov*, and *Andersson-Darling* tests *were* considered nonparametric because they do not require the data to meet the usual parametric assumptions and because their purpose is to test whether a specific distribution comes from a normal distribution.

All normality tests indicate that the data do not come from a normal distribution, so when comparing with the non-parametric *Kruskal-Wallis* technique, the following results were found:

data: average per career

Kruskal-Wallis chi-squared = 18.886, df = 14, p-value = 0.1694

The *p-value* in the three tests is greater than *0.05*, indicating that there is no statistically significant evidence to reject the null hypothesis. Therefore, the differences between the medians of the different majors are not significant for any of the factors evaluated: "Impact and benefit of using IAG tools"; "Familiarity and perception of IAG use"; and "Ethical considerations, privacy, and the future of IAG." It can therefore be stated that perceptions or assessments do not vary significantly among students from different majors.

The graph in Figure 3 visually shows why the result of the *Kruskal-Wallis* test was not significant; the similarity in the medians and the overlap of the distributions support the statistical conclusion that there are no significant differences between the factors evaluated and the majors. On the other hand, the outliers do not seem sufficient to indicate clear differences between groups.

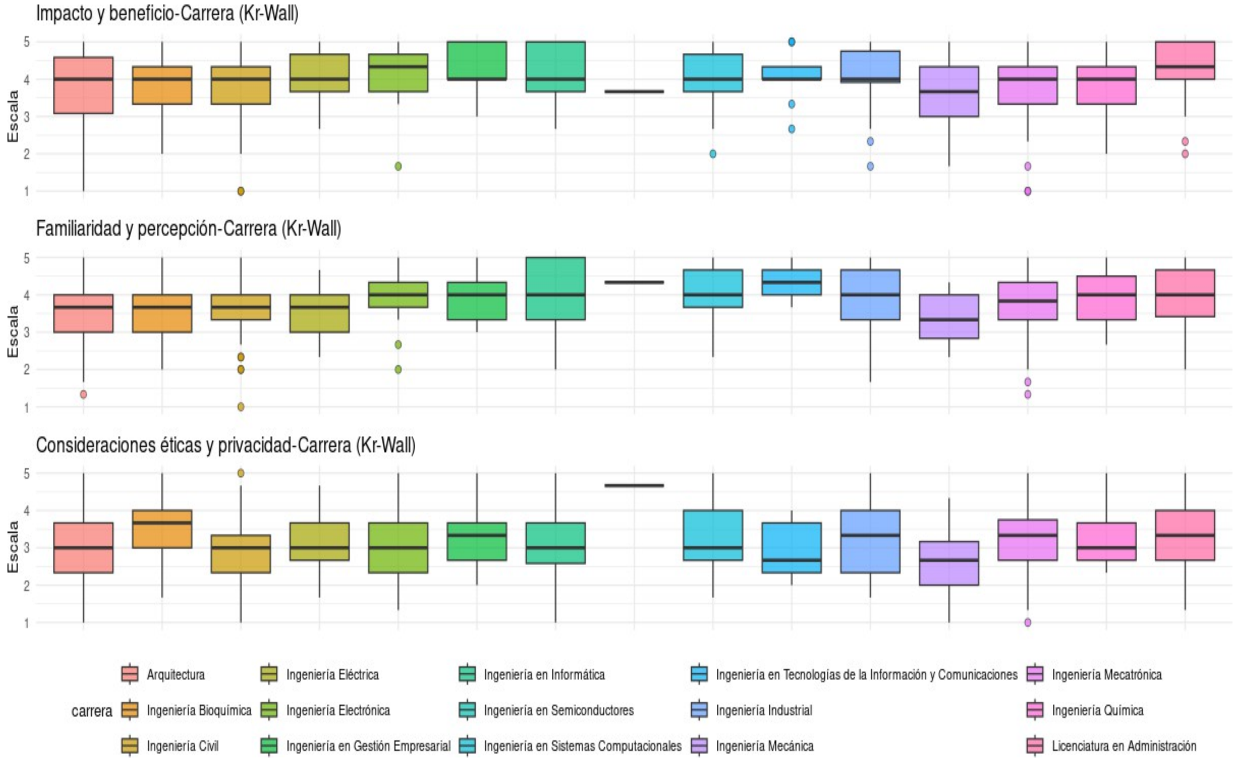

***Figure 3**. No difference between factors by major. Kruskal-Wallis test.*

***Source**: Own elaboration (2024).*

In general, students use generative artificial intelligence tools mainly to support the learning processes they face in higher education.

From the results presented, it can be interpreted that higher education students believe that the use of IAG tools does have an impact and benefit on their learning process; furthermore, that they are familiar with the use of these tools. This leads to the discussion of whether this use and benefit that they argue is really ethical; it is monitored by teachers to identify whether there is really learning taking place in the student.

In their research, Niño Carrasco, Castellanos Ramírez, Perezchica Vega, and Sepúlveda Rodríguez (2025) state that 67.14% of students surveyed are familiar with IAG tools. Similarly, when asked if it improves academic performance, 62.86% of students agree that it saves them time in presenting their academic work. These results are similar to those found in the study in this article.

It is striking that students show a lack of interest in ethical issues and data privacy when using IAG tools. Here, it is worth analyzing whether this indifference is due to the productivity that the use of these tools offers them, which makes them think that these aspects are of little value, coinciding with what Párraga Rocero, Vargas Bálcazar, Rocero Benavides, Palacios Vaicilla, and Capelo Andrade mention (2024), students may not be using them responsibly and effectively, or they may simply be tempted to use them as a shortcut to complete tasks without in-depth analysis.

In contrast, and with regard to the ethics of using IAG tools, the study by Niño Carrasco, Castellanos Ramírez, Perezchica Vega, and Sepúlveda Rodríguez (2025) argues that 75.35% of students point out the need to be guided by a teacher who teaches them about the proper ways to identify how far they are allowed to use them, and 65.71% are concerned about use, addiction, and inappropriate use.

This coincides with what Párraga Rocero, Vargas Bálcazar, Rocero Benavides, Palacios Vaicilla, and Capelo Andrade (2024) express: IAGs transform learning processes; however, it is necessary to evaluate whether they really develop critical skills and comprehensive training in students. It is the job of teachers and institutions to regulate this process.

Personally, as teachers, tutors, and workers in an educational institution, we must monitor, regulate, and even be positively suspicious of their use in order to truly achieve assertive learning.

As a reflection, we agree with García Peñalvo, Llorens Largo, and Vidal (2023), who mention that there is no question as to whether IAG tools are suitable for learning because their use, benefits, familiarity, and perception are evident. however, their exposure and access should be considered a reflection of the intelligence of the subject who uses them and of the evaluator, in this case the student and teacher.

We agree with the reflections of Salguero Barba and García Salguero (2024) that the use of IAG should not be considered a threat to human intelligence, but rather as a tool that contributes to improving the quality of learning in students and making them more productive and better performers.

When evaluating the hypothesis that there is no statistically significant difference, the results obtained show that the degree program does not matter and that the stated hypothesis is accepted. Among students studying different bachelor's degree programs with respect to the use of IAG tools, measured in the three factors identified: impact and benefit of using IAG tools for learning; familiarity and perception of the use of IAG for learning; and ethical considerations, privacy, and the future of IAG for learning, there is no difference between students from different higher education programs at the Durango Institute of Technology.

CONCLUSIONS

This article collected data using a *Likert* scale instrument that measured the use of generative artificial intelligence tools by higher education students at the Durango Institute of Technology in their learning.

The stratified sample collected meets the 95% confidence level with a 5% error, which allowed for the corresponding analyses to be carried out as set out in the initial objectives.

The instrument was applied through forms on the *Google Form* platform using awareness-raising strategies; it consisted of 12 *items* measuring the variable of use and exposure to IAG tools for learning. This variable was measured in three factors: the impact and benefit of using IAG tools for learning; familiarity and perception of the use of IAG for learning; and ethical considerations, privacy, and the future of IAG for learning.

The instrument meets acceptable reliability standards, with a *Cronbach's* coefficient of approximately 0.77. Similarly, the instrument satisfies validity criteria, as it was evaluated using *Kaiser-Meyer-Olkin* and *Bartlett* tests for factor analysis, which indicate that the questions validly measure the established dimensions.

The results show that students agree and do consider that there is an impact and benefit in the use of IAG tools; they also consider that they are familiar with and have an understanding of the use of these tools; however, where they do not entirely agree is on the ethical aspects and data privacy, as well as on the uncertainty of the future of IAG tools.

The *Shapiro-Wilk*, *Kolmogorov-Smirnov,* and *Anderson-Darling* tests were applied to detect whether the data did not come from a normal distribution. All tests indicate that the data are not normal.

Given these tests of data normality, the article reflects the results of the nonparametric *Kruskal-Wallis* test, which answers the question: Is there a significant difference in the use of IAG tools among students in different professional careers? The answer is that there is no difference. On the other hand, the null hypothesis (*Ho*) is accepted: there are no significant differences between students studying different undergraduate majors with respect to the use of IAG tools.

Finally, it is emphasized that the specific objectives set out at the beginning were achieved.

FUTURE WORK

It is recommended that this survey be replicated in other educational institutions using the same methodology described above in order to observe whether the instrument meets reliability and validity criteria. In addition, the resulting statistics should be analyzed and compared, the non-normality of the data should be verified, and the aforementioned hypothesis should be evaluated using the data collected.

With the data presented in the raw.githubusercontent.com/rpizarrog/analitica_de_datos/refs/heads/main/datos/datos.csv , it is recommended to replicate the reliability and validity tests, calculate the statistics described, test the normality of the data, and compare factors in relation to the professional career.

As future work, it is recommended that this survey be applied at another time in the same institution to observe and compare results; it is suggested that it be carried out in another higher education institution with humanities degrees to observe and compare results.

With regard to the instrument, it is recommended that it serve as a basis for considering similar questions and similar factors that measure the use of generative artificial intelligence tools by higher education students and that this be reflected in their learning.

REFERENCES

Alpizar Garrido, L. O., & Martínez Ruiz, H. (2024). Perspective of upper secondary students on the use of generative artificial intelligence in their learning. *Ride Ibero-American Journal for Educational Research and Development, 14*(28). doi:https://doi.org/10.23913/ride.v14i28.1830

Anderson, D., Sweneey, D., & Williams, T. (2008). *Statistics for Management and Economics* (10th ed.). Mexico City: Cengage Learning Editores S.A. de C.V.

Angles Canlla, O. L., & Angles Canlla, V. E. (2024). Challenges and opportunities of using AI in university teaching from an ethical perspective. *Latin American Journal of Social Sciences and Humanities LATAM*, 377.

Bartlett, M. S. (1950). Tests of significance in factor analysis. British Journal of Psychology. *American Psychological Association APS*, 77-85.

Corredera, J. R. (2023). Generative Artificial Intelligence. *Annals of the Royal Academy of Doctors of Spain.* , Volume 8, number 3 – 2023, pages 475-489 .

García Peñalvo, F. J., Llorens Largo, F., & Vidal, J. (2024). The new reality of education in the face of advances in generative artificial intelligence. (A. I. Distancia, Ed.) *RIED-Ibero-American Journal of Distance Education, 27*(1). doi:https://doi.org/10.5944/ried.27.1.37716

García Sánchez, O. V. (June 2023). Use and perception of ChatGPT in higher education. (U. A. Sinaloa, Ed.) *RITI Journal, 11*(23). doi:https://doi.org/10.36825/RITI.11.23.009

Hernández Sampieri, R., Fernández Collado, C., & Baptista Lucio, M. (2010). *Research Methodology.* McGrawn Hill.

Hernández Sampieri, R., Fernández Collado, C., & Baptista Lucio, M. d. (2014). *Research Methodology.* Mexico: McGraw Hill Education.

Hollander, M., Wolfe, D. A., & Chicken, E. (2013). Nonparametric Statistical Methods (3rd ed.). John Wiley & Sons.

Kaiser, H. F. (1974). An index of factorial simplicity. Psychometrika. *APA PsycNet. American Psychological Association*, 31-36. doi:https://doi.org/10.1007/BF02291575

Leslie, K. (1965). *Survey Sample.* John Wiley & Sons.

López Aguado, M., & Gutiérrez Provecho, L. (2019). How to perform and interpret exploratory factor analysis using SPSS. (U. d. ICE, Ed.) *Journal of Innovation and Research in Education. ISSN: 2013-2255*. Retrieved from file:///C:/Users/Admin/Downloads/27057-Text%20de%20l'article-61418-4-10-20190701.pdf

Martínez González, M. A. (September 2023). Responsible use of artificial intelligence in university students: A recnoetic perspective. (C. d. Educativos, Ed.) *Revista Boletín REDIPE, 12*(9), 172-178. Retrieved April 15, 2024

Menacho Ángeles, M. R., Pizarro Arancibia, L. M., Osorio Menacho, J. A., Osorio Menacho, J. A., & León Pizarro, B. L. (2024). Artificial intelligence as a tool for autonomous learning in higher education students. *INVECOM Journal "Transdisciplinary Studies in Communication and Society, 4*(2). Retrieved April 5, 2024, from www.revistainvecom.org

Niño Carrasco, S. A., Castellanos Ramírez, J. C., Perezchica Vega, J. E., & Sepúlveda Rodríguez, J. A. (January 15, 2025). University students' perceptions of the uses of artificial intelligence in education. *Fuentes Journal, 27*(1), 94-106. Retrieved from https://doi.org/10.12795/revistafuentes.2025.26356

Párraga Rocero, W. J., Vargas Bálcazar, K. S., Rocero Benavides, M. M., Palacios Vaicilla, T. E., & Capelo Andrade, S. S. (2024). ChatGPT artificial intelligence and its influence on the learning outcomes of upper secondary education students. *Latin American Journal of Social Sciences and Humanities LATAM*, 2290.

Pérez, E., & Medrano, L. (2010). Exploratory Factor Analysis: Conceptual and Methodological Foundations. *Argentine Journal of Behavioral Sciences (RACC)*, 58-66.

Posit Cloud. (2024). *Friction-free data science.* Retrieved from R Studio Cloud: https://posit.cloud/ Quijano García, J. E. (2024). Development of an evaluation model to measure the impact of AI-based generative text tools in higher education.

Thesis submitted as a requirement for the Master's Degree in Information Systems Management and Technological Projects. Bogotá, Colombia: EAN University.

Rojas Villafuerte, Á. V. (2024). Attitudes and use of generative text AIs among university students. *Southern Manabí State University. Faculty of Health Sciences, Nursing program*. Jipijapa, Manabí, Ecuador.

Salguero Barba, N. G., & García Salguero, C. P. (2024). Artificial intelligence-based knowledge management for the transformation of educational institutions. *Latin American Journal of Social Sciences and Humanities LATAM*, 1713.

COLLABORATIVE WORK TABLE

Conceptualization	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad
Methodology	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad
Software	Pizarro Gurrola Rubén, Rodríguez Rivas José Gabriel
Validation	Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad, Calzada Terrones Jeorgina, Rodríguez Rivas José Gabriel
Formal Analysis	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad, Calzada Terrones Jeorgina, Rodríguez Rivas José Gabriel
Research	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad, Calzada Terrones Jeorgina, Rodríguez Rivas José Gabriel
Resources	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad, Calzada Terrones Jeorgina, Rodríguez Rivas José Gabriel
Data curation	Pizarro Gurrola Rubén, Rodríguez Rivas José Gabriel
Writing - Preparation of the original draft	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad, Calzada Terrones Jeorgina, Rodríguez Rivas José Gabriel

Writing - Review and editing	Pizarro Gurrola Rubén, Moorillón Soto Ana Louisa, Domínguez Flores Araceli Soledad, Calzada Terrones Jeorgina, Rodríguez Rivas José Gabriel
Visualization	Pizarro Gurrola Rubén, Rodríguez Rivas José Gabriel
Supervision	Pizarro Gurrola Rubén, Rodríguez Rivas José Gabriel