Research Article

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Predictive Model to Evaluate University Students' Perception and Attitude Towards Artificial Intelligence

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Abstract

Artificial Intelligence is emerging as a transformative tool impacting various industries, including education As Artificial Intelligence continues to develop and gain prominence in classrooms, understanding how students perceive this integration and how it affects their educational experience becomes crucial. The aim of this research was to develop a model to predict the perception of students at Bolívar State University regarding the use and potentialities of Artificial Intelligence in the educational field. The methodology employed a factorial analysis, which represents the relationships among a set of variables. From this, a logistic regression was performed, generating an equation to identify predictors that allowed understanding student behavior based on specific characteristics such as attitude, perception, and satisfaction. As a technique for information gathering, a questionnaire composed of 25 items on a Likert scale was used, statistically validated with a Cronbach's alpha value of 0.925. The results of the model show that all covariates, except "Insecurity and fear of using artificial intelligence tools", are significant ($p < 0.001$). This suggests that the remaining variables are related to the dependent variable "Positive Perception of the Usefulness of Artificial Intelligence in Learning". It is concluded that students have limited knowledge about Artificial Intelligence, and this may cause them to have unrealistic expectations. Training can help students learn about AI and how to use it effectively and ethically.

Keywords: *artificial intelligence, attitude, higher education, perception, predictive model*

1. Introduction

Artificial Intelligence (AI) is a technology that is transforming the world (Zhang & Lu, 2021). In the field of education, it is being used to personalize learning, provide support to students, and automate tasks (Vidal et al., 2015; Sherif et al., 2023). In this context, the integration of AI represents one of the most promising developments in education (Salas-Pilco et al., 2022), as it has led to innovative educational resources such as personalized learning, intelligent tutoring, chatbots, and more (Barroso et al., 2012; Carrera & Bonilla, 2022). This is altering learning experiences and the automating responsibilities in educational institutions (Kamalov et al., 2023; Çağataylı & Çelebi, 2022). Bearing this in mind, it is significance to reflect on the importance and implications of integrating AI in education, as it has the potential to transform the way we learn (Tai, 2020).

The educational field has benefited from AI advancements by leveraging its capabilities to provide better learning outcomes for students (Barrios-Tao et al., 2021). The application of AI in education holds great potential, but it is important that it be integrated appropriately into autonomous educational systems (Lei et al., 2017). This is because formal education can provide students with basic knowledge, but it is the student who decides how to enrich their learning through their environment (Castillejos, 2022). On the other hand, there are also ethical and social implications that must be considered when integrating AI in education. Potential challenges include data security, privacy, the teacher-student relationship, and bias in AI algorithms (Arias et al., 2021; Al-tkhayneh et al., 2023).

AI is being integrated into the educational field, creating new teaching and learning methods with the aim of making educational environments increasingly dynamic (Dzimińska et al., 2018; Silva-González et al., 2021). Therefore, AI should be a tool that supports students in developing their skills, it should not determine the success of their learning. Students should be the protagonists of their own learning and develop their own cognitive and ethical skills (Eaton et al., 2018), but also educators need to prioritize digital literacy and AI training to foster an interactive and efficient learning ecosystem (Joseph et al., 2024). The new applications of AI can assist educators in identifying the strengths and weaknesses of each student, as well as their challenges and motivations, to create personalized learning pathways (Lee et al., 2023).

Education is the foundation for a better future because it provides students with the tools they need to succeed. It teaches them to think critically, solve problems, communicate effectively, and work as a team. While also instilling ethical, civic, and sustainability values (Gaber et al., 2023; Weiss et al., 2021). Therefore, the inclusion of AI in education seeks to improve the teaching-learning process, providing a personalized, efficient, and effective experience (González, 2023). As AI technologies continue to develop and gain prominence in classrooms, it is essential to understand how students perceive this integration and how it affects their educational experience (K. Zhang & Aslan, 2021; Barrett & Pack, 2023). AI tools have more efficient evaluation systems; for instance, Coskun & Alper (2024) demonstrated in their study that AI-based evaluation systems can provide objective and consistent feedback. The growing importance of AI in the global education sector has led more researchers to explore this topic; among the most analysed areas are AI for personalized learning, skill development through AI, and student interaction with these tools (Artemova, 2024).

Various studies have addressed the integration of AI in the educational context, through the development of statistical models that include factor analyses and logistic regressions. The purpose of these studies is to understand the perceptions and attitudes of students regarding this integration (Paek & Kim, 2021). Such research has considered a range of characteristics such as gender, age, grade level, school, and class (Chai et al., 2023; Jokhan et al., 2022). The sample size for these studies ranges from 500 to 3.000 participants; in some cases, teachers and administrative staff are also included as subjects of study (Assi et al., 2019; Mora Zambrano et al., 2018). Most of these research efforts focus on predicting student behavior, demonstrating that the integration of AI must consider the needs and satisfaction of students to facilitate the continuous development of their competencies (Cerasoli et al., 2016; Chamorro-Atalaya et al., 2023).

Students' perceptions of the integration of artificial intelligence (AI) in education vary, but research shows that it has a positive impact on their academic development. For example, the study by Teng (2024) highlights how English as a foreign language students prefer to use AI to edit and proofread their writing, allowing them to efficiently improve the clarity and cohesion of their texts. Yuwono et al. (2024) highlight the role of co-creation in promoting AI literacy and innovation among teachers, demonstrating that experiential learning and collaborative design processes can effectively bridge the knowledge gap. On the other hand, Saihi et al. (2024) and Al Murshidi et al. (2024) point out that despite the generally positive perception of the benefits of AI-based chatbots in higher education, some concerns arise, particularly regarding data security, potential biases in chatbot responses, and the risk of excessive dependence on technology. Additionally, Gruenhagen et al. (2024) in their study found the need for modern education to be accompanied by clear policies and guidelines regarding the ethical use of generative AI in education. The integration of AI in education is transforming teaching, making it essential to address both the positive and negative perceptions of students.

The present study aimed to present a predictive model to examine how students at Bolívar State University perceive the integration of AI in their learning process. This model was developed in response to the growing need to understand the attitudes, expectations, and concerns of students regarding the inclusion of AI in education (Ayuso & Gutiérrez, 2022). In a world where technology is increasingly present in education, it is important to be aware of its implications and to address them in a responsible and ethical manner (Kooli, 2023; Arabit-García et al., 2021). In this way, it ensures that AI is integrated into education positively (Unesco, 2023).

This study not only contributes to the understanding of student perceptions, but also offers essential insights for creating effective strategies aimed at incorporating AI in the educational context. This technology is transforming the world, and its influence on our lives will continue to grow in the future (Friedrich et al., 2022;.Lalaleo-Analuisa et al., 2021). Therefore, it is crucial to ensure that its incorporation in the educational field is beneficial, satisfactory, and above all, ethical for all those involved (Gruetzemacher & Whittlestone, 2022). The predictive model in this article represents a significant advancement in that direction, and its results are detailed in the subsequent sections of the paper.

2. Methodology

2.1 Design

The study adopted a cross-sectional, non-experimental design, as it focuses on observing and describing relationships between variables without manipulating them or establishing causality. The approach of this research was quantitative, which is based on the collection of numerical data through methods such as interviews, questionnaires, or surveys. These data are statistically analyzed to identify patterns and trends (Del Canto & Silva, 2013). The study used an inductive method, because through the collection of data and its subsequent analysis, it was possible to identify patterns or trends that lead to the formulation of broader theories or principles, that is, it moved from the specific to the general (Hurtado & Toro, 2007). In this case, the perceptions of the students under study provided a general overview regarding the use and potentialities of AI in the educational context.

This research reached a predictive level because it developed a model that included a factorial analysis, which represents the relationships among a set of variables and posits that these relationships can be explained by a series of unobservable variables, called factors (Ferrando & Anguiano, 2010). Factor analysis is a statistical method used to reduce a large number of variables into fewer underlying factors, which represent patterns or structures within the data. By identifying these factors, the analysis helps to simplify the relationships between variables, making it easier to interpret the data (Kooptiwoot et al., 2024; Pizarro Romero & Martínez Mora, 2020). Factor analysis

was conducted using the principal component method (Rodríguez Garcés et al., 2019), which allowed for the identification of the underlying factors influencing students' perceptions of AI. To validate this analysis, the Kaiser-Meyer-Olkin (KMO) Test, with a value of 0.891, confirmed the adequacy of the sample, while Bartlett's Test of Sphericity indicated significant correlations among the variables, justifying the application of factor analysis.

Once the key factors were identified through the factor analysis, a logistic regression model was implemented to explore the predictive relationships between the variables. Logistic regression is a technique that allows for the prediction of the value of a categorical dependent variable based on one or more independent variables (Acosta-Gonzaga et al., 2020). Logistic regression is particularly useful in educational research when the outcome is categorical, such as predicting whether students perceive AI as beneficial or not (Díaz-Martínez et al., 2021). In this case, the model examined how attitudes toward AI, perceived skills in creating AI projects, and satisfaction with AI use in virtual settings could predict students' positive perception of the utility of AI in learning.

The regression model was validated through additional tests, such as the Kolmogorov-Smirnov test to assess data normality and the Spearman correlation test to examine the linear relationships between the predictor variables and the dependent variable.

2.2 Participants

The study population for this research consisted of all students in the Faculty of Education at the UEB, numbering 1500 individuals. The degrees offered by this faculty include: Intercultural Bilingual Education, Early Childhood Education, Computer Science Pedagogy, Basic Education, Mathematics and Physics Pedagogy, and Pedagogy of National and Foreign Languages.

Given the nature and size of the population, a simple random sampling approach was chosen to obtain a representative sample. Calculations were made with a 2.95% margin of error and a 95% confidence level. The sample consisted of 840 individuals randomly distributed among the various degrees of the faculty.

The general formula used to determine the sample size (n) in a finite population was:

$$n = \frac{N*Z^2*p*(1-p)}{E^2*(N-1)+Z^2*p*(1-p)}$$

- N: is the population size (1500 in this case).
- Z: is the z-value for the desired confidence level (for a 95% confidence level, Z≈1.96).
- p: is the estimated proportion of the population with the characteristic of interest (if unknown, 0.5 is used to maximize the sample size).
- E: is the margin of error (in this case, 0.0295 for 2.95%).

$$n = \frac{1500*1{,}96^2*0{,}5*(1-0{,}5)}{0{,}0295^2*(1500-1)+1{,}96^2*0{,}5*(1-0{,}5)}$$

$$n = \frac{1443{,}90}{2{,}2664} \approx 637$$

The previous formula provides a larger sample size for small populations. To adjust it to the final size, the finite population and the margin of error must be considered. Thus, with a population of 1500, the calculated sample size is adjusted to approximately 840 to achieve the desired margin of error.

Once the sample size was calculated, simple random sampling was used to select 840 students from the total population. This means that each student had an equal probability of being selected, ensuring that the sample was representative of the population.

In the study conducted with 840 students from a higher education institution, the sample was predominantly female, with 73% women compared to 27% men. In terms of age, the majority of students, 85%, are in the 18 to 27 years range, while 8% are between 28 and 37 years old. Only 4% of the students are in the 38 to 47 years range, and a small fraction (3%) are over 47 years old. These demographic data allowed for an in-depth analysis of students' perceptions and attitudes towards the use of artificial intelligence in educational settings, exploring how these characteristics influence the

evaluation of AI's potential and impact on their learning and training.

2.3 Information Collection Procedure

The questionnaire was administered virtually through Google Forms. It was applied exclusively to students to understand their perception regarding the integration of AI in their teaching-learning process. Subsequently, follow-up was conducted via email to ensure that the information provided by the students was reliable.

2.4 Instrument

As a technique for data collection, a questionnaire adapted from Ayuso & Gutiérrez (2022) was used. It consisted of 25 items on a Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). This questionnaire included demographic questions and multiple-choice items. The reliability of the instrument was assessed by calculating the Cronbach's alpha coefficient for all items in the questionnaire. The final reliability obtained was satisfactory, reaching a value of 0.925.

2.5 Data Analysis Plan

SPSS is a software that enables users to perform statistical data analysis. It can be used for a variety of purposes, including data description, exploration of relationships between variables, outcome prediction, and data visualization (Xiao et al., 2015). For the data analysis, version 24 of SPSS was used. Initially, it was necessary to apply statistical tests to determine if the collected data were suitable as a basis for developing a factorial analysis.

The initial step involved identifying a comprehensive list of variables relevant to the study's focus on AI integration in education. This was guided by the literature review and expert consultations to ensure all pertinent aspects were considered. Variables were translated into measurable items on a Likert scale within a structured questionnaire. The items were designed to capture various dimensions of students' perceptions and attitudes towards AI in education. To refine the questionnaire, a pilot test was conducted with a small sample of students. Feedback from this pilot was used to adjust and ensure that the items were clear and relevant, improving the reliability of the data collection instrument.

These tests used were the Kaiser-Meyer-Olkin (KMO) Test and the Bartlett's Test of Sphericity to determine the adequacy of the data for factor analysis. The former is a measure of the suitability of data for factor analysis; it measures the sampling adequacy for each variable. KMO values between 0.8 and 1 indicate that the sampling is adequate; values below 0.6 indicate that the sampling is not adequate, and corrective measures should be taken (Benites, 2021). The lower the proportion, the more suitable the data are for factor analysis.

The Bartlett's Test of Sphericity, on the other hand, compares an observed correlation matrix with the identity matrix. In other words, it checks for redundancy among variables that can be summarized with a few factors. In a factor analysis, this test was used to verify that a data reduction technique could compress the data representatively (Romero & Mora, 2021).

In factor analysis, it is also necessary to calculate the value of communality, which can predict what proportion of the variable's variance is the result of the principal components or the correlations between each variable and individual values. Based on this, the factor analysis was developed, ensuring that its resulting values did not present biases in the data. This analysis groups data as factors and validates constructs to determine if there is a mathematical relationship between each of the questions. Thus, both the predictor variables and the independent variable can be defined.

Logistic regression also required preliminary calculations to assess the normality of the data and detect differences among them. This calculation was the Kolmogorov-Smirnov test, which allowed for

measuring the degree of agreement between the distribution of the collected data set. Additionally, it serves as a guide to determine what types of tests can be applied in logistic regression; in this case, non-parametric measures can be applied.

Considering this, it was necessary to apply the Spearman's Rho test to identify if the predictor variables, previously defined in the factor analysis, have any correlation with the dependent variable. Furthermore, Goodness of Fit tests were necessary to indicate that the model, along with its covariates, is representative in terms of predicting the positive perception of the use of AI in students' learning.

3. Results

The results highlight the importance of this study in the development of a model to examine the perception and attitudes of students regarding the use of AI in teaching and training environments. This allows us to explore how the model translates into robust predictions and to assess its impact in terms of the application and potential of AI in the educational field, based on the attitude, ability, and satisfaction of the students belonging to this higher education institution.

The data collected from 840 students in the study include information from both male and female students of various ages. These data indicate that, of the total number of students, 27% are male and the remaining 73% are female. With respect to age, 85% of the students are in the age range of 18 to 27 years; 8% are in the age range of 28 to 37 years; only 4% of the students are between 38 and 47 years old, and a small minority (3%) are over 47 years old.

3.1 Factorial Model

3.1.1 Preliminary Calculations

The results of the Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity are adequate for conducting a factor analysis. The KMO value of 0.891 is quite high and suggests that the data have an underlying structure that can be decomposed through factor analysis. In turn, Bartlett's Test of Sphericity rejects the null hypothesis that the variables are uncorrelated, supporting the presence of relationships among the variables and justifying the execution of a factor analysis.

Table 1. Kaiser-Meyer-Olkin and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.891
Bartlett's Test of Sphericity	Approx. Chi-Square	13786.681
	Df	300
	Sig.	0.000

In the development of a factor analysis, it is necessary to measure communalities, which are a useful measure in this type of analysis for predicting the value of a variable. The communalities values after extraction vary, but are mostly reasonably high, indicating that most of the variables are related to the extracted factors. However, it is worth noting that some variables have lower communalities, such as "I can design an Artificial Intelligence project with help" (0.517) and "The information about Artificial Intelligence is so much that I find it difficult to remember the important points" (0.567). These variables may not be as related to the extracted factors and might require additional consideration in the analysis.

Table 2. Communalities Values

N.	Items	Initial	Extraction
1	The use of Artificial Intelligence is simple and clear	1.000	0.595
2	Learning to create Artificial Intelligence projects is easy for me	1.000	0.711
3	Using Artificial Intelligence for learning is a good idea	1.000	0.66
4	Artificial Intelligence makes learning more interesting	1.000	0.733
5	Using Artificial Intelligence for learning is fun	1.000	0.678
6	I would like to use Artificial Intelligence as a tool for studying	1.000	0.752
7	The use of Artificial Intelligence during classes would facilitate my understanding of certain concepts	1.000	0.579
8	With the use of Artificial Intelligence in subjects, my performance would increase	1.000	0.611
9	I have the necessary resources to create Artificial Intelligence projects in my future work	1.000	0.622
10	I can design an Artificial Intelligence project with help (tutorial, people…)	1.000	0.517
11	I can design an Artificial Intelligence project without help	1.000	0.716
12	I can design an Artificial Intelligence project if I have time to do the task	1.000	0.595
13	I enjoy creating Artificial Intelligence projects	1.000	0.681
14	Completing an Artificial Intelligence project gives me a sense of satisfaction and achievement	1.000	0.618
15	I feel insecure when using the Artificial Intelligence project creation tool	1.000	0.778
16	The use of the Artificial Intelligence project creation tool somehow intimidates me	1.000	0.761
17	Successfully completing an Artificial Intelligence lesson would be important to me	1.000	0.637
18	I would like my teachers to use Artificial Intelligence for my training	1.000	0.767
19	I intend to use the Artificial Intelligence project creation tool	1.000	0.740
20	I enjoy Artificial Intelligence lessons so much that I would like to learn more about this subject	1.000	0.797
21	The virtual modality of the seminars has facilitated the learning of the contents worked on	1.000	0.652
22	There is so much information about Artificial Intelligence that I find it difficult to remember important points	1.000	0.567
23	I find that the use of Artificial Intelligence can be useful for student learning	1.000	0.769
24	I would recommend the use of Artificial Intelligence for the teaching-learning process	1.000	0.696
25	Artificial Intelligence projects allow students to acquire knowledge more quickly	1.000	0.574

3.1.2 Factor Extraction

Using the principal component method, the factors of the model have been extracted. The matrix shows the initial eigenvalues, the sums of squared loadings for extraction, and the sums of squared loadings for rotation. The initial eigenvalues represent how much variance is explained by each component. Component 1 has the highest eigenvalue (10.059) and explains 40.235% of the total variance. Component 2 explains 8.435% of the variance, and so on.

The cumulative percentage of variance shows how much variance is accumulated as additional components are added. For example, the first two components explain 48.670% of the variance, the first three 56.309%, and so forth. The results reveal that the first three or four principal components explain a substantial amount of variance. This suggests that working with these principal components can be considered to simplify and summarize the underlying structure of the data.

Table 3. Total explained variance

Component	Initial eigenvalues			Sums of squared extraction loadings			Sums of squared rotation loadings		
	Total	% variance	% cumulative	Total	% variance	% cumulative	Total	% variance	% cumulative
1	10.059	40.235	40.235	10.059	40.235	40.235	4.949	19.796	19.796
2	2.109	8.435	48.670	2.109	8.435	48.670	4.329	17.317	37.113
3	1.910	7.639	56.309	1.910	7.639	56.309	3.337	13.350	50.463
4	1.598	6.394	62.703	1.598	6.394	62.703	2.119	8.475	58.938
5	1.139	4.555	67.258	1.139	4.555	67.258	2.080	8.320	67.258
6	0.943	3.771	71.030						
7	0.786	3.145	74.174						
8	0.736	2.946	77.120						
9	0.667	2.669	79.789						
10	0.580	2.319	82.108						
11	0.519	2.076	84.184						
12	0.487	1.948	86.132						
13	0.465	1.860	87.993						
14	0.400	1.598	89.591						
15	0.367	1.468	91.059						
16	0.357	1.428	92.488						
17	0.312	1.248	93.736						
18	0.273	1.092	94.828						
19	0.248	0.992	95.820						
20	0.233	0.930	96.750						
21	0.197	0.787	97.537						
22	0.184	0.734	98.271						
23	0.166	0.664	98.935						
24	0.143	0.573	99.508						
25	0.123	0.492	100.000						

The rotated matrix with the VARIMAX method shows the factor loadings of the questionnaire items on each of the five principal components. These results are discussed below:

Component 1: This component is associated with the positive perception and usefulness of artificial intelligence in the learning process. Items related to the use of artificial intelligence to facilitate understanding, increase performance, and make learning more interesting and fun have significant loadings in this component.

Component 2: This component relates to the attitude towards AI in teaching and training. Items related to the preference for teachers to use artificial intelligence, the intention to use project creation tools, and the importance of completing AI lessons have significant loadings on this component.

Component 3: This component is linked to the perception of skills in the creation of artificial intelligence projects. Items reflecting confidence in creating artificial intelligence projects, either with or without assistance, have significant loadings on this component.

Component 4: This component is linked to the attitude towards learning to create artificial intelligence projects. Items related to learning and enjoyment of project creation have significant loadings in this component.

Component 5: This component is related to the perception of insecurity and fear when using artificial intelligence project creation tools, as well as the difficulty in remembering important points about artificial intelligence.

Table 4. Model components

N.	Item	Component				
		1	2	3	4	5
6	I would like to use Artificial Intelligence as a tool for studying	0.772	0.222	0.091	0.304	0.077
4	Artificial Intelligence makes learning more interesting	0.754	0.180	0.221	0.288	-0.001
3	Using Artificial Intelligence for learning is a good idea	0.754	0.253	0.124	0.019	-0.134
5	Using Artificial Intelligence for learning is fun	0.708	0.214	0.356	-0.004	0.068
7	The use of Artificial Intelligence during classes would facilitate my understanding of certain concepts	0.680	0.190	0.236	0.154	-0.012
8	With the use of Artificial Intelligence in subjects, my performance would increase	0.680	0.156	0.101	0.337	0.026
23	I find that the use of Artificial Intelligence can be useful for student learning	0.665	0.543	0.096	-0.013	0.151
18	I would like my teachers to use Artificial Intelligence for my training	0.229	0.804	0.208	0.158	-0.011
19	I intend to use the Artificial Intelligence project creation tool	0.154	0.763	0.236	0.252	-0.123
17	Successfully completing an Artificial Intelligence lesson would be important to me	0.198	0.751	0.092	0.088	0.131
20	I enjoy Artificial Intelligence lessons so much that I would like to learn more about this subject	0.209	0.677	0.136	0.501	-0.158
24	I would recommend the use of Artificial Intelligence for the teaching-learning process	0.529	0.624	0.153	-0.048	0.023
25	Artificial Intelligence projects allow students to acquire knowledge more quickly	0.440	0.573	0.196	0.024	0.115
11	I can design an Artificial Intelligence project without help	0.019	0.040	0.845	-0.021	-0.012
9	I have the necessary resources to create Artificial Intelligence projects in my future work	0.237	0.192	0.713	0.032	0.140
12	I can design an Artificial Intelligence project if I have time to do the task	0.216	0.327	0.641	0.174	0.025
2	Learning to create Artificial Intelligence projects is easy for me	0.377	-0.064	0.592	0.463	0.023
10	I can design an Artificial Intelligence project with help (tutorial, people...)	0.266	0.322	0.563	0.099	0.128
13	I enjoy creating Artificial Intelligence projects	0.251	0.356	0.541	0.442	-0.052
21	The virtual modality of the seminars has facilitated the learning of the contents worked on	0.192	0.376	0.001	0.672	0.151
1	The use of Artificial Intelligence is simple and clear	0.412	0.035	0.392	0.517	-0.054
14	Completing an Artificial Intelligence project gives me a sense of satisfaction and achievement	0.330	0.427	0.335	0.462	-0.038
15	I feel insecure when using the Artificial Intelligence project creation tool	-0.014	-0.130	0.127	0.059	0.861
16	The use of the Artificial Intelligence project creation tool somehow intimidates me	-0.050	-0.028	-0.004	0.130	0.861
22	There is so much information about Artificial Intelligence that I find it difficult to remember important points	0.130	0.300	0.037	-0.227	0.638

3.1.3 Model generation

The model integrates these five components to provide a comprehensive view of students' perceptions and attitudes towards artificial intelligence in learning. These components reflect key dimensions that can influence the adoption and acceptance of artificial intelligence in the educational field.

Component 1: Positive Perception of the Utility of Artificial Intelligence in Learning

This component is based on the students' positive perception of the usefulness of artificial intelligence in the learning process. The items included in this component reflect the idea that students view artificial intelligence as a valuable tool that makes learning more interesting, enjoyable, and effective.

Component 2: Attitude Towards Artificial Intelligence in Teaching and Training

This component focuses on students' attitudes towards the role of artificial intelligence in teaching and training. The items in this component indicate that students prefer teachers to use artificial intelligence, intend to use project creation tools related to artificial intelligence, and value the importance of completing lessons in this field.

Component 3: Perception of Skills in Creating Artificial Intelligence Projects

This component is based on students' perceptions of their ability to create artificial intelligence projects. The items in this component indicate that students feel confident in their capacity to design artificial intelligence projects, whether independently or with assistance, provided they have the resources and time for the task.

Component 4: Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence

This component focuses on students' perceptions of the virtual learning modality and their

satisfaction with using artificial intelligence. The items in this component reflect the idea that students find the virtual modality to be effective and that the use of artificial intelligence provides them with satisfaction and a sense of achievement.

Component 5: Insecurity and Fear in the Use of Artificial Intelligence Tools

This component is based on students' perceptions of insecurity and fear when using artificial intelligence tools. The items in this component indicate that students feel insecure about using these tools and may experience some fear or intimidation in doing so.

3.2 Regression Analysis

The model requires combining the items of each variable into a "whole". To achieve this, the sum of the scores for each factor or category of the model is calculated. This provides an overall scalar score for each of the mentioned categories, which is used in the regression analysis proposed in the current study. The regression equation considers category 1 (Positive Perception of the Utility of Artificial Intelligence in Learning) as the dependent variable and the remaining factors as predictors.

3.2.1 Preliminary Calculations

Table 5 shows the results of the Kolmogorov-Smirnov normality test. It is observed that there is no normality in any data series (Sig. < 0.05), therefore, it is appropriate to apply robust estimation methods and non-parametric tests.

Table 5. Kolmogorov-Smirnov Normality Test

Category	Kolmogorov-Smirnov		
	Statistic	df	Sig.
Positive Perception of the Utility of Artificial Intelligence in Learning	.176	830	.000
Attitude Towards Artificial Intelligence in Teaching and Training	.129	830	.000
Perception of Skills in Creating Artificial Intelligence Projects	.141	830	.000
Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence	.172	830	.000
Insecurity and Fear in the Use of Artificial Intelligence Tools	.137	830	.000

Using the Spearman coefficient, correlation tests are conducted to verify if the predictors have a linear relationship with the dependent variable. This is seen in Table 6, where it can be observed that there is a significantly positive correlation (correlation coefficient = 0.644, p-value < 0.001) between "Attitude Towards Artificial Intelligence in Teaching and Training" and "Positive Perception of the Utility of Artificial Intelligence in Learning". This suggests that as the attitude towards artificial intelligence in teaching and training becomes more positive, the positive perception of the utility of artificial intelligence in learning tends to be higher.

A significantly positive correlation was found (correlation coefficient = 0.511, p-value < 0.001) between "Perception of Skills in Creating Artificial Intelligence Projects" and "Positive Perception of the Utility of Artificial Intelligence in Learning". This indicates that as the perception of skills in creating artificial intelligence projects increases, the positive perception of the utility of artificial intelligence in learning tends to be higher.

There is a significantly positive correlation (correlation coefficient = 0.599, p-value < 0.001) between "Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence" and "Positive Perception of the Utility of Artificial Intelligence in Learning". This suggests that as the perception of the virtual modality and satisfaction in the use of artificial intelligence increase, the positive perception of the utility of artificial intelligence in learning tends to be higher.

Although there is a negative correlation between "Insecurity and Fear in the Use of Artificial Intelligence Tools" and "Positive Perception of the Utility of Artificial Intelligence in Learning"

(correlation coefficient = -0.037), this correlation is not significant (p-value = 0.285). This shows that "Insecurity and Fear in the Use of Artificial Intelligence Tools" is not significantly related to "Positive Perception of the Utility of Artificial Intelligence in Learning."

These correlations support the selection of a linear regression model, as they show significant linear relationships between the three predictor variables (attitude, perception of skills, and satisfaction in virtual modality) and the dependent variable (positive perception of the utility of artificial intelligence in learning). Therefore, a linear regression model is appropriate to explore the influence of these variables on the positive perception of the utility of artificial intelligence in learning.

Table 6. Spearman's Rho Test

			Attitude Towards Artificial Intelligence in Teaching and Training	Perception of Skills in Creating Artificial Intelligence Projects	Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence	Insecurity and Fear in the Use of Artificial Intelligence Tools
Spearman's Rho	Positive Perception of the Utility of Artificial Intelligence in Learning	Correlation Coefficient	.644	.511	.599	-.037
		Sig. (2-tailed)	.000	.000	.000	.285
		N	840	840	830	840

3.2.2 Model Development for Regression

Before analyzing the results obtained in the regression analysis, it is important to note that the dependent variable "Positive Perception of the Utility of Artificial Intelligence in Learning" is in a range from 7.00 to 35.00, with a mean of 27.3506 and a standard deviation of 5.10670.

In turn, the predictors are characterized by the following descriptive statistics:

- Attitude Towards Artificial Intelligence in Teaching and Training: This variable has a range from 6.00 to 30.00, with a mean of 22.8422 and a standard deviation of 4.49505.
- Perception of Skills in Creating Artificial Intelligence Projects: This variable has a range from 6.00 to 30.00, with a mean of 19.6434 and a standard deviation of 4.80431.
- Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence: This variable has a range from 3.00 to 15.00, with a mean of 10.8614 and a standard deviation of 2.35946.
- Insecurity and Fear in the Use of Artificial Intelligence Tools: This variable has a range from 3.00 to 15.00, with a mean of 9.5470 and a standard deviation of 2.50588.

Table 7. Dependent Variable and Covariates

Variables		**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Dependent Variable	Positive Perception of the Utility of Artificial Intelligence in Learning	830	7.00	35.00	27.3506	5.10670
Covariate	Attitude Towards Artificial Intelligence in Teaching and Training	830	6.00	30.00	22.8422	4.49505
	Perception of Skills in Creating Artificial Intelligence Projects	830	6.00	30.00	19.6434	4.80431
	Perception of Virtual Modality and	830	3.00	15.00	10.8614	2.35946

Variables		N	Minimum	Maximum	Mean	Std. Deviation
	Satisfaction in the Use of Artificial Intelligence					
	Insecurity and Fear in the Use of Artificial Intelligence Tools	830	3.00	15.00	9.5470	2.50588

The regression model that has been fitted shows adequate goodness of fit. The likelihood ratio chi-square statistic (659.614) with 4 degrees of freedom is significant ($p < 0.001$). This indicates that the overall model, which includes all covariates, is statistically significant in predicting the positive perception of the utility of artificial intelligence in learning.

Table 8. Goodness of Fit Values

Goodness of Fit	Value	df	Value/df
Deviance	9765.495	825	11.837
Scaled Deviance	830.000	825	
Pearson's Chi-square	9765.495	825	11.837
Scaled Pearson's Chi-square	830.000	825	
Log Likelihood	-2200.771		
Akaike Information Criterion (AIC)	4413.541		
Corrected AIC for finite samples (AICC)	4413.643		
Bayesian Information Criterion (BIC)	4441.870		
Consistent AIC	4447.870		

Table 9. Omnibus Test

Likelihood Ratio Chi-square	df	Sig.
659.614	4	.000

The model effects tests show that all covariates, except for "Insecurity and Fear in the Use of Artificial Intelligence Tools", are significant ($p < 0.001$). This suggests that the variables "Attitude Towards Artificial Intelligence in Teaching and Training," "Perception of Skills in Creating Artificial Intelligence Projects," and "Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence" have a relationship with the dependent variable.

This calculation corroborates the results of the correlation analysis, where it was determined that the component "Insecurity and Fear in the Use of Artificial Intelligence Tools" does not have a significant relationship with the dependent variable, and therefore, does not contribute to the model. For this reason, it will be removed from the model.

Table 10. Model Effects Tests

Source	Type III		
	Wald Chi-square	df	Sig.
(Intercept)	50.240	1	.000
Attitude Towards Artificial Intelligence in Teaching and Training	55.935	1	.000
Perception of Skills in Creating Artificial Intelligence Projects	15.314	1	.000
Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence	43.423	1	.000
Insecurity and Fear in the Use of Artificial Intelligence Tools	.320	1	.572

Finally, the Multiple Regression Analysis (Robust Model) concludes with the estimation of the model. For this, the regression equation is formed with the results from Table 11:

Table 11. Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-square	df	Sig.
(Intercept)	6.749	.9522	4.883	8.615	50.240	1	.000
Attitude Towards Artificial Intelligence in Teaching and Training	.420	.0562	.310	.530	55.935	1	.000
Perception of Skills in Creating Artificial Intelligence Projects	.198	.0506	.099	.297	15.314	1	.000
Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence	.628	.0953	.441	.815	43.423	1	.000
Insecurity and Fear in the Use of Artificial Intelligence Tools	.031	.0540	-.075	.136	.320	1	.572
(Scale)	11.766[a]	.5776	10.686	12.954			

The regression equation is as follows:

Positive Perception of Utility = 6.749 + (0.420 * Attitude Towards Artificial Intelligence) + (0.198 * Perception of Skills in Creating Artificial Intelligence Projects) + (0.628 * Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence)

3.2.3 Interpretation of the Regression Equation

The regression equation indicates that the positive perception of the utility of artificial intelligence in learning can be predicted based on the remaining predictor variables. The regression coefficients indicate how much the positive perception of utility changes when the predictor variables increase by one unit.

- Attitude Towards Artificial Intelligence in Teaching and Training: For each additional unit in attitude towards artificial intelligence, the positive perception of utility increases by 0.420 units.
- Perception of Skills in Creating Artificial Intelligence Projects: For each additional unit in perception of skills in creating artificial intelligence projects, the positive perception of utility increases by 0.198 units.
- Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence: For each additional unit in perception of virtual modality and satisfaction in the use of artificial intelligence, the positive perception of utility increases by 0.628 units.

In this analysis, the relationship between the positive perception of the utility of artificial intelligence in learning and the predictor variables "Attitude Towards Artificial Intelligence in Teaching and Training," "Perception of Skills in Creating Artificial Intelligence Projects," and "Perception of Virtual Modality and Satisfaction in the Use of Artificial Intelligence" has been evaluated. The variable "Insecurity and Fear in the Use of Artificial Intelligence Tools" has been excluded due to its lack of statistical significance. The remaining predictor variables have been shown to be statistically significant and are supported by the existing literature in this context.

4. Discussion

The regression equation indicates that students are receptive to the integration of Artificial Intelligence in their learning process. For Castillejos (2022), this positive inclination is based on the

belief that AI has the potential to improve the learning experience of students, in addition to supporting their academic performance. On the other hand, Terrones (2022), in his study on AI and its constructive ethical evaluation, states that students also have ethical and privacy concerns that need to be adequately addressed to ensure an effective implementation of AI in classrooms. Students' concerns about the ethical issues of AI in education underscore the need to address them adequately (Kooli, 2023). Educators and educational institutions must take these concerns into account and develop policies and practices that protect student privacy and ensure ethical use of AI in the classroom (Anishchenko et al., 2023).

Students' current lack of experience in using AI-based technology raises the need to provide learning and training opportunities. According to Lei et al. (2017), in their study on improving learning efficiency through the flipped classroom, mentions that this can help bridge the gap between expectations and reality regarding the use of AI in education. AI learning and training programs provide students with the knowledge and skills needed to use AI tools effectively (Barrios-Tao et al., 2021; Al-tkhayneh et al., 2023). This would enable them to take advantage of these tools by improving their learning and academic performance (Jiménez, 2021). In addition, learning programs help students feel more confident and comfortable using AI, which would allow them to take advantage of their full potential (Hidalgo et al., 2021).

The model presented in this study predicts whether students believe that AI is useful for learning, based on satisfaction with use and attitude. In their study, Chai et al. (2023) on modeling behavioral intentions point out that AI curricula should focus on students' needs and their satisfaction, so that they can learn and grow in the field of AI. Based on this, Jokhan et al. (2022) asserts that a prediction model is accurate, precise, and complete enough to predict student behaviors in virtual education systems. This is because learners perceive the use of AI as a tool that streamlines the learning process, in addition to describing changes to a system, such that a task can be performed more effectively the next time it is performed (Friedrich et al., 2022; Tuomi, 2018).

Similarly, to this study, Al Murshidi et al. (2024) employed a factorial analysis approach to identify relevant scales related to perceptions of the benefits, limitations, and risks of using AI. They underscore the importance of integrating AI into education to motivate students towards future improvements and responsible use of the technology. In parallel, Alpizar Garrido & Martínez Ruiz (2024) in their descriptive study, found that 73.4% of students view AI as an innovative tool for deeper and easier comprehension of topics. Hence, like this research, they recommend that educators continue to develop pedagogical strategies to optimize the use of AI in the classroom. Frutos et al. (2024) and Morán-Ortega et al. (2024) , in their respective articles, also considered students' and teachers' perceptions regarding the benefits and limitations of AI. They found common ground in recognizing the benefits of AI, such as task simplification, translation, and code review, while also highlighting ethical risks, lack of training, plagiarism, and the potential for excessive dependence on these technologies. However, the comparison of findings with other studies is largely positive, as confirmed by Joseph et al. (2024) in their study on digital literacy, which analyzed 409 students and found a significant correlation with positive perceptions, demonstrating that AI in educational settings enhances the learning experience.

These findings are relevant for educators and educational policy makers, as they provide important information about how students perceive and expect AI to be integrated into their educational process (Silva-González et al., 2021). Therefore, the results of this research are relevant for educational area and public policies (González, 2023). AI integration strategies should be based on the needs and concerns of students, in addition to ensuring that AI in education is accessible and beneficial to all (Rodriguez, 2021; Salas-Pilco et al., 2022).

4.1 Study Limitations

It is necessary to mention that this study relies on students' self-perception, which implies that the responses reflect personal perceptions and attitudes, rather than solid and objective knowledge about

AI. Nevertheless, these data are important to understand how students relate to and experience AI in the educational context. It is crucial to consider that perception can vary depending on cultural differences and the educational context. The diversity of the students participating in the study may affect their responses.

Although the study has some limitations, the results are still valuable for understanding student opinions about AI in education. This information is essential to guide future strategies for implementing AI in the educational field, ensuring an effective response to the needs and concerns of students. While the data are subjective, they reflect the actual experience of the students. This information is crucial for designing educational interventions that are effective and dynamic for students.

5. Conclusion

Artificial intelligence can be a powerful tool for learning, but it is important that it is used responsibly and ethically. Key findings from the research indicate that students see artificial intelligence as a powerful tool for learning, but have concerns about privacy, fairness, and security. They also believe that artificial intelligence can help them access information more easily and quickly. However, training students in artificial intelligence and adopting sound educational policies are critical to ensure that artificial intelligence is used to benefit everyone in the educational environment.

This model contributes to predict students' perception of the use of artificial intelligence in the learning process, as a function of attitudes, skills and satisfaction in educational environments. These findings are consistent with the literature suggesting that a positive attitude towards technology and satisfaction with its use are predictors of a positive perception of its usefulness in education. The model can be used to identify areas where artificial intelligence has the potential to benefit students, as well as areas where concerns may arise. This information can be used to make informed decisions on how to integrate AI ethically and effectively from the classroom to educational policy making.

This study, based on students' self-perceptions, reflects personal views and attitudes rather than objective knowledge about AI. Despite this limitation, the data offer valuable insights into how students relate to and experience AI in educational settings. Perceptions may vary due to cultural differences and educational contexts, with participant diversity potentially affecting responses. While the study's limitations must be acknowledged, the findings are crucial for guiding future AI implementation strategies in education, addressing student needs and concerns. The subjective nature of the data highlights the importance of considering students' actual experiences when designing effective and dynamic educational interventions.

Future lines of research should combine objective measurements of AI skills with students' self-reported opinions to gain a more complete understanding of how they comprehend and interact with AI. Additionally, cross-cultural studies analyzing how different educational and cultural contexts influence students' perceptions of AI, as well as longitudinal studies tracking the evolution of these perceptions and their use over time, would provide valuable insights into the long-term impact of AI in education. Finally, investigating the role of teachers and administrators, along with the ethical and data security implications, would help develop more robust frameworks for AI integration in education.

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