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Prediction of the use of generative artificial intelligence through ChatGPT among Costa Rican university students: A PLS model based on UTAUT2

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Abstract: The rise of generative artificial intelligence (GenAI) is transforming education, with tools like ChatGPT enhancing learning, content creation, and academic support. This study analyzes ChatGPT's acceptance among Costa Rican university students using the UTAUT2 model and partial least squares structural equation modeling (PLS-SEM). The research examines key predictors of AI adoption, including performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual usage. Data from 194 students reveal that performance expectancy is the strongest predictor of behavioral intention, followed by effort expectancy, while social influence and facilitating conditions play a minor role. Behavioral intention significantly influences actual usage. Differences emerge based on gender and age, with male students and those aged 21-30 showing higher acceptance levels. Despite positive attitudes toward ChatGPT, students report a lack of sufficient training for its effective use. These findings highlight the need for tailored pedagogical strategies to ensure meaningful AI integration into education. The study suggests further research on AI training programs and their long-term impact on academic performance, emphasizing the importance of fostering digital literacy for a more effective and responsible adoption of generative AI in higher education.

Keywords: ChatGPT; AI acceptance; UTAUT2; higher education; digital literacy

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1. Introduction

The emergence of generative artificial intelligence (GenAI) in the educational field is having a significant impact on teaching practices and students' learning processes. This type of artificial intelligence is characterized by its ability to process natural human language and generate content in various formats, such as text, images, and audio. As [1] (p. 2) points out, "generative models process a large corpus of complex and unstructured data, such as texts, audio, or images, to then generate new content in the same style as the original data." Similarly, [2] (p. 7) states that "it refers to a distinct class of artificial intelligence that uses deep learning models to generate human-like content, such as images or words, in response to complex and varied instructions." This content can be produced in a wide variety of formats (video, text, audio, etc.) and serve different functions (assigning labels to images, clustering data—such as identifying customer segments with similar purchasing behaviors—or selecting actions) [3].

The use of GenAI in educational contexts has been facilitated by the accessibility of tools based on advanced language models, whose intuitive interface allows interactions through natural language. However, this ease of use does not imply that its educational application is automatically effective. As UNESCO [4] warns, the effective use of these tools requires specific training in both query formulation and the interpretation and refinement of generated responses. In this regard, a transition in the application of technology in teaching is observed: from a model focused on learning "from" technology, where it is perceived merely as a channel for transmitting information and assessment, to a paradigm of learning "with" technology, where its use is enhanced as a cognitive tool for knowledge construction [5].

Despite its growing incorporation into education, the implementation of GenAI presents various challenges and limitations. Among these, the accuracy and validity of generated information, ethical responsibility in its use, the need for curricular adaptation, the redefinition of teaching and student roles, and the presence of inherent biases in AI models stand out. Additionally, aspects such as randomness in responses, dependence on these tools, the need for specific training to critically evaluate their results, and implications for data privacy and security must be considered [6, 7, 8]. In this last aspect, there are two major models: in one, control is held by companies, as seen in the United States, while in the other, control is exercised by the state, as in China.

Among the most widely used GenAI tools in the educational environment are OpenAI's ChatGPT, Microsoft's Copilot, Deepseek by Hangzhou DeepSeek Artificial Intelligence Basic Technology Research, and Google's Gemini. These platforms offer a wide range of functionalities, including text generation, image creation, document translation, summarization and evaluation rubrics, key idea identification, case correction, assistance in computer programming, and information synthesis, among others. This versatility has made GenAI an attractive resource for integration into teaching, transforming traditional teaching and learning methodologies [9, 10]

The rise in the use of GenAI in education has led to an increase in research on its pedagogical applications and has driven meta-analyses on its impact in various educational contexts [11, 12, 13, 14, 15]. These systematic reviews have identified key trends, such as the predominance of studies focused on higher education, the concentration of research in developed countries, teachers' concerns about ethical aspects, the interest in analyzing students' practices with these tools, the recognition of their potential for adaptive learning, and the identification of a widespread need for training in their use. Additionally, both teachers and students express a positive attitude toward the incorporation of GenAI in teaching, provided that its use is carried out critically and reflectively [16, 17].

To conclude this section, it is worth highlighting Robert & Muscanell [18] in their Horizon Report for Educause: "… generative artificial intelligence emerged as the fastest-adopted technology in history. All members of the higher education community, from students to administrators, are trying to determine what impact generative AI tools can, will, and should have on life, learning, and work." [18] (p. 3).

2. Students and ChatGPT

In this regard, artificial intelligence (AI) represents a field of particular interest, given its exponential growth and increasing integration into teaching and learning processes. Exploring students' attitudes and level of acceptance toward this technology in general, and ChatGPT in particular, not only helps to understand their disposition toward these technologies but is also essential for identifying necessary changes in AI education, the measures that should be adopted to optimize their training in this field, and the possibilities that, according to students, these technologies have for their incorporation into their educational activities.

The incorporation of AI into education has been carried out under three paradigms: AI-directed, where the student is a recipient; AI-supported, where the student is a collaborator; and AI-empowered, where the student is a leader. In these three paradigms, AI techniques are used to address educational and learning problems in different ways. AI is used to represent knowledge models and guide cognitive learning while students act as recipients of AI services in Paradigm One; AI is used to support learning while students collaborate with AI in Paradigm Two; AI is used to empower learning while students take the initiative to learn in Paradigm Three [19].

Numerous studies have shown that students exhibit positive attitudes and strong interest in the possibilities AI offers for their education, as well as an increasing willingness to integrate these tools into their learning [20, 21, 16, 22, 23].

However, research results have sometimes been contradictory. Some studies indicate that AI use decreases students' academic performance [24], although this may be due to poor pedagogical planning by teachers or the unrestricted use of these tools by students without proper guidance. Nevertheless, studies showing positive performance outcomes outnumber those indicating negative results [25, 26].

Furthermore, research based on the application of the UTAUT model has highlighted that factors such as hedonic motivation, performance expectancy, effort expectancy, and social influence are key predictors of students' intention to use ChatGPT. In this regard, [27] found that behavioral intention and facilitating conditions significantly influence the actual use of this tool. Similar findings were reported by [28], who observed that usage behavior has the most significant impact on behavioral intention, followed by performance expectancy and hedonic motivation. Additionally, behavioral intention significantly influences actual usage, being modulated by habit and facilitating conditions.

Finally, although students exhibit a high acceptance of AI in general and ChatGPT in particular, they also acknowledge insufficient training for its effective use [20, 29]. In this regard, various studies have pointed out that students demand greater training in this field, emphasizing the need for structured and specific education on the use of AI in educational contexts [21]. These demands highlight the importance of designing educational strategies that enable the effective pedagogical integration of AI, ensuring that students acquire the necessary competencies for its critical and reflective use in academic settings.

3. Methods

3.1. Objectives

The main objective of this study is to analyze the factors influencing the acceptance and use of artificial intelligence by Latin American university students, specifically Costa Rican students, based on the UTAUT2 model and using a partial least squares structural equation modeling (PLS-SEM) approach.

To achieve this purpose, the following specific objectives are established:

- Evaluate "Performance Expectancy" (PE) in the intention to use artificial intelligence in the university context, considering students' perceptions of the usefulness of tools like ChatGPT in their learning process.
- Analyze "Effort Expectancy" (EE) and its impact on AI acceptance, examining whether the simplicity of interaction with these technologies facilitates their adoption.
- Determine "Social Influence" (SI) in the intention to use AI, exploring the role that academic and social opinions and recommendations play in students' willingness to use artificial intelligence.

- Examine the effect of "Facilitating Conditions" (FC) on AI adoption, identifying the availability of resources, technological knowledge, and institutional support as key factors in the implementation of these tools.
- Measure "Behavioral Intention" (BI) and its relationship with "Usage Behavior" (UB) in artificial intelligence, analyzing whether students' willingness to use these tools translates into effective use in the educational field.
- Validate the structure of the UTAUT2 model in the context of higher education in Latin America, assessing the robustness of the model through the analysis of factor loadings, discriminant validity, and global fit using SRMR.

3.2. Research Sample

The study sample consists of a total of 194 Costa Rican university students, distributed according to various sociodemographic and academic characteristics. Regarding gender, the majority of participants are women (n=124, 63.9%), while men account for 36.1% (n=70).

In terms of age, the largest group corresponds to students aged 21 to 30 years (n=99, 51.0%), followed by those aged 18 to 20 years (n=57, 29.4%). Participants aged 31 to 40 years constitute 10.8% (n=21), while those aged 41 to 50 years and over 50 years represent 4.1% (n=8) and 4.6% (n=9), respectively.

Regarding the field of study, there is a higher representation of students from Health Sciences (n=73, 37.6%), followed by those from Social Sciences (n=39, 20.1%), Engineering (n=32, 16.5%), and Economic Sciences (n=22, 11.3%). Students from Arts and Humanities (n=15, 7.7%), Basic Sciences (n=11, 5.7%), and Agri-Food Sciences (n=2, 1.0%) have a smaller representation in the sample.

Finally, regarding the type of university, 54.1% (n=105) of the participants are from public universities, while 45.9% (n=89) are enrolled in private institutions.

The research was conducted between November 2024 and January 2025.

3.3. Data Collection Instrument

The data collection instrument used in this study was designed following the UTAUT2 model, adapted to assess the degree of acceptance of artificial intelligence in the university setting, specifically regarding the use of ChatGPT. The questionnaire was developed based on the constructs of the model, ensuring the theoretical validity of the measurement and its applicability in the educational context. The questionnaire was administered via an online platform (Google Forms), facilitating access to a larger number of participants and ensuring efficient data collection. Before participating, students provided informed consent, ensuring compliance with the ethical principles of research.

The questionnaire consists of 19 items distributed across different dimensions of the UTAUT2 model.

- The first dimension, "Academic Performance Expectancy" (PE), evaluates students' perceptions of ChatGPT's usefulness in their academic performance. It includes four items exploring the tool’s impact on productivity, speed in completing tasks, and its contribution to achieving academic goals.
- The second dimension, "Effort Expectancy" (EE), measures the perceived ease of use of ChatGPT, considering the clarity of interaction and the ease of learning the tool, with a total of four items.
- The third dimension, "Social Influence" (SI), consists of three items that investigate the extent to which the opinions and recommendations of close individuals influence students' adoption of ChatGPT.

- The fourth dimension, "Facilitating Conditions" (FC), gathers information on the availability of resources and necessary knowledge for using artificial intelligence, as well as the compatibility of the tool with other technologies used by students. This dimension also includes one item regarding the possibility of receiving external support in case of difficulties with the tool.

Finally, the "Behavioral Intention" (BI) and "Usage Behavior" (UB) dimensions assess students' future willingness to continue using ChatGPT in their studies. The first consists of three items measuring the intention to keep using the tool over time, while the second collects information on the actual frequency of ChatGPT use in the academic context.

Table 1 presents the different items that make up the instrument.

Table 1. Items of the Measurement Instrument.

Item	Mean	SD
PE1 I believe ChatGPT is useful in my studies	6,11	1,346
PE2 Using ChatGPT increases your chances of achieving important things in your studies	5,43	1,650
PE3 Using ChatGPT helps you complete tasks and projects faster in your studies	6,09	1,424
PE4 Using ChatGPT increases your productivity in your studies	5,61	1,613
EE1 Learning to use ChatGPT is easy for me	6,17	1,376
EE2 My interaction with ChatGPT is clear and understandable	6,05	1,326
EE3 I find ChatGPT easy to use	6,31	1,221
EE4 It is easy for me to acquire skills in using ChatGPT	5,97	1,454
SI1 The people who are important to me think that I should use ChatGPT	4,49	1,990
SI2 The people who influence my behavior believe that I should use ChatGPT	4,26	2,065
SI3 The people whose opinions I value prefer that I use ChatGPT	4,23	2,087
FC1 I have the necessary resources to use ChatGPT	6,54	1,068
FC2 I have the necessary knowledge to use ChatGPT	6,14	1,394
FC3 ChatGPT is compatible with the technologies I use	6,47	1,161
FC4 I can get help from others when I have difficulties using ChatGPT	5,69	1,742
BI1 I intend to continue using ChatGPT in the future	6,06	1,491
BI2 I will always try to use ChatGPT in my studies	4,87	2,010
BI3 I plan to keep using ChatGPT frequently	5,30	1,862
UB1 Choose your frequency of use for ChatGPT	4,46	1,688

Regarding the mean scores and standard deviations obtained in each of the dimensions, Table 2 presents a summary of the descriptive statistics for the UTAUT2 model dimensions:

Table 2. Mean Scores and Standard Deviations.

Dimension	Mean	SD
Performance Expectancy (PE)	5,81	1,303
Effort Expectancy (EE)	6,13	1,160
Social Influence (SI)	4,33	1,933
Facilitating Conditions (FC)	6,21	1,059
Behavioral Intention (BI)	5,41	1,651
Usage Behavior (UB)	4,46	1,688

3.4. Data Analysis Procedure

For data analysis, structural equation modeling (SEM) was employed using partial least squares (PLS-SEM) with SmartPLS software. This approach was selected due to its ability to model complex relationships between latent and observed variables, allowing for the simultaneous assessment of the validity of the UTAUT2-based theoretical model and the influence of its constructs on university students' acceptance of artificial intelligence.

First, the validity and reliability of the measurement model were assessed through factor loadings analysis, considering a minimum threshold of 0.70 for item acceptance. Additionally, the internal consistency of each construct was verified using Cronbach's alpha and composite reliability (CR), with an acceptance criterion set above 0.70. Convergent validity was confirmed using average variance extracted (AVE), ensuring values above 0.50.

To ensure discriminant validity, the Fornell-Larcker criterion was applied, comparing the square root of AVE with the correlations between constructs. After validating the measurement model, the structural model analysis was conducted, evaluating the significance and magnitude of path coefficients using the bootstrapping procedure with 5,000 resamples. Determination coefficients (R^2) were calculated to estimate the explained variance of endogenous variables, and f^2 values were used to assess the effect size of each predictor.

Additionally, the Standardized Root Mean Square Residual (SRMR) was incorporated as a global model fit indicator. An SRMR value below 0.08 was considered a good fit criterion, allowing for an evaluation of the discrepancy between the observed and estimated covariance matrices.

4. Results

To begin with, in order to validate the factorial structure of the model, a factor loadings analysis of the items was conducted, ensuring that all loadings were close to 0.7, [30] which guarantees adequate convergent validity (Table 3).

Table 3. Factor Loadings.

	BI	EE	FC	PE	SI	UB
BI1	0.858					
BI2	0.939					
BI3	0.954					
EE1		0.847				
EE2		0.885				
EE3		0.868				
EE4		0.835				
FC1			0.879			
FC2			0.893			
FC3			0.650			
FC4			0.693			
PE1				0.895		
PE2				0.857		
PE3				0.825		
PE4				0.839		
SI1					0.904	
SI2					0.964	
SI3					0.941	
UB						1.000

The results confirm adequate convergent validity of the measurement model, as most items exhibit factor loadings above 0.7, indicating that each item significantly contributes to its respective construct.

For behavioral intention (BI), factor loadings range between 0.858 and 0.954, reflecting a strong correlation between the items and the construct. Perceived ease of use (EE) also shows high values, with loadings between 0.835 and 0.885.

Regarding facilitating conditions (FC), three of its items show adequate values (FC1 and FC2 above 0.87), although FC3 (0.650) and FC4 (0.693) exhibit slightly lower loadings, which might suggest a weaker contribution of these items to the construct.

Performance expectancy (PE) presents factor loadings ranging from 0.825 to 0.895, while social influence (SI) displays particularly high values, with loadings above 0.90 for all its items.

Finally, actual use (UB) has a value of 1.000, indicating that it is measured with a single item.

The internal consistency of the constructs was also confirmed using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE).

The values are presented in Table 4.

Table 4. Internal Consistency.

	Cronbach's alpha	**Composite reliability**	**Average variance extracted (AVE)**
BI	0.906	0.908	0.843
EE	0.882	0.889	0.738
FC	0.800	0.923	0.618
PE	0.877	0.884	0.730
SI	0.930	0.936	0.877

The results confirm the adequate internal consistency of the model's constructs [31]. First, all Cronbach's alpha values exceed the recommended threshold of 0.7, indicating high internal reliability of the items within each construct. In particular, the social influence (SI) construct shows the highest value (0.930), followed by behavioral intention (BI) with 0.906, reflecting strong coherence among its items.

The composite reliability (CR) also reaches satisfactory values in all cases, exceeding the 0.7 threshold and approaching or surpassing 0.9 in several constructs, reinforcing the robustness of the model.

Finally, the AVE (average variance extracted), which measures the amount of variance explained by the items relative to the error, presents values above the minimum criterion of 0.5, except for facilitating conditions (FC), which shows a value of 0.618—slightly lower than the others but still within acceptable ranges.

Subsequently, discriminant validity was assessed using the Fornell-Larcker criterion (Table 5). According to this criterion, a construct should share more variance with its own indicators than with other constructs in the model. This is confirmed when the square root of the AVE for each construct (values on the diagonal) is greater than the correlations between constructs (values outside the diagonal).

Table 5. Fornell-Larcker Criterion.

	BI	**EE**	**FC**	**PE**	**SI**	**UB**
BI	0.918					
EE	0.580	0.859				
FC	0.511	0.662	0.786			

PE	0.757	0.550	0.543	0.854		
SI	0.483	0.381	0.283	0.584	0.937	
UB	0.613	0.498	0.432	0.534	0.359	1.000

Subsequently, discriminant validity was assessed using the Fornell-Larcker criterion (Table 5). According to this criterion, a construct should share more variance with its own indicators than with other constructs in the model. This is confirmed when the square root of the AVE for each construct (values on the diagonal) is greater than the correlations between constructs (values outside the diagonal).

In this case, all diagonal values exceed the correlations with other constructs, indicating adequate discriminant validity. In particular, behavioral intention (BI) presents a diagonal value of 0.918, which is higher than its correlations with the other variables, with the highest correlation being with performance expectancy (PE) (0.757).

Similarly, effort expectancy (EE) has a square root of AVE of 0.859, with moderate correlations with the other variables, particularly its relationship with facilitating conditions (FC) (0.662). Likewise, the social influence (SI) construct exhibits the highest level of independence (0.937), with relatively low correlations with the other dimensions.

Once the measurement model was validated, the relationships between constructs were analyzed using structural equation modeling (PLS-SEM) (Figure 1).

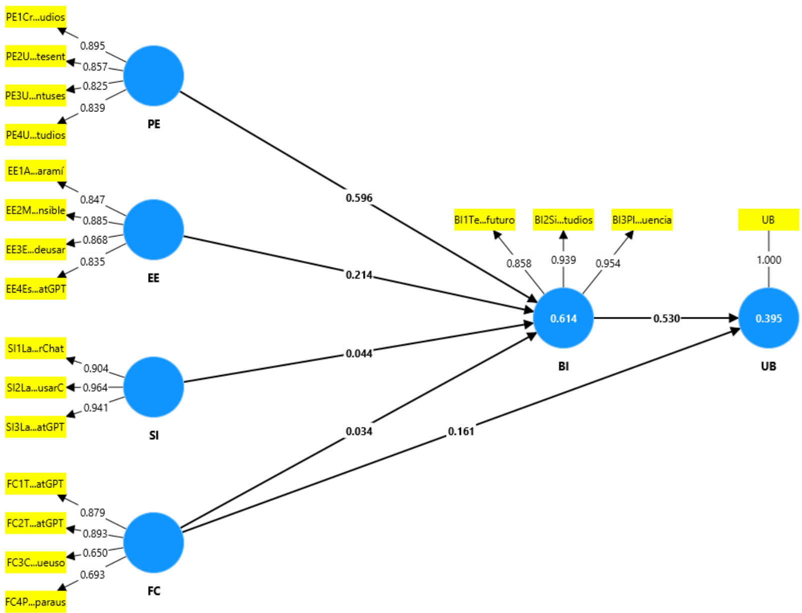

Figure 1. Structural Model.

The most relevant result is the strong influence of performance expectancy (PE) on behavioral intention (BI), with a coefficient of 0.596, suggesting that students perceive the usefulness of AI as a key factor in its adoption. Similarly, behavioral intention (BI) has a significant impact on actual use (UB), with a coefficient of 0.530, confirming that intention is a direct predictor of usage behavior.

Effort expectancy (EE) also shows a positive relationship with behavioral intention (BI) (0.214), although to a lesser extent than performance expectancy. On the other hand, social influence (SI) and facilitating conditions (FC) have a much lower impact on behavioral intention (0.044 and 0.034, respectively), suggesting that these factors are not primary determinants in students' intention to adopt AI. However, facilitating conditions (FC) exhibit a more relevant effect on actual use (UB) (0.161), indicating that access to resources and technical support may influence the effective adoption of AI in the academic environment.

Additionally, the model explains 64.4% of the variance in behavioral intention (BI) and 39.5% of the variance in actual use (UB), indicating a moderate-to-high explanatory power in predicting AI adoption in the university context.

To evaluate the statistical significance of the path coefficients, the bootstrapping method with 5,000 resamples was applied (Table 6).

Table 6. Path Coefficients.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> UB	0.530	0.527	0.092	5.746	0.000
EE -> BI	0.214	0.219	0.103	2.079	0.001
FC -> BI	0.034	0.038	0.088	0.384	0.001
FC -> UB	0.161	0.165	0.079	2.041	0.031
PE -> BI	0.596	0.591	0.099	5.999	0.000
SI -> BI	0.044	0.046	0.093	0.469	0.023

The results confirm that most path coefficients are statistically significant, as their p-values are below 0.05. In particular, the strong influence of performance expectancy (PE) on behavioral intention (BI) stands out, with a coefficient of 0.596 and a t-value of 5.999, indicating a robust and highly significant relationship ($p = 0.000$). Similarly, behavioral intention (BI) has a considerable impact on actual use (UB), with a coefficient of 0.530 and a t-value of 5.746, reaffirming its role as a key predictor of adoption behavior.

Effort expectancy (EE) also shows a significant relationship with behavioral intention (BI) ($\beta = 0.214$, $t = 2.079$, $p = 0.001$), although its impact is lower than performance expectancy. On the other hand, facilitating conditions (FC) have a significant effect on actual use (UB) ($\beta = 0.161$, $t = 2.041$, $p = 0.031$), suggesting that access to resources and support influences the effective use of AI. However, its impact on behavioral intention (BI) is very low and not significant ($\beta = 0.034$, $t = 0.384$, $p = 0.001$).

Social influence (SI), with a coefficient of 0.044 and a t-value of 0.469, shows a weak relationship with behavioral intention, although it remains statistically significant ($p = 0.023$). This suggests that peer perception has a minor impact on students' adoption of AI.

Finally, to evaluate the overall model fit, the Standardized Root Mean Square Residual (SRMR) was analyzed, yielding a value of 0.062. This result indicates a good model fit, as it falls below the recommended threshold of 0.08 in the PLS-SEM literature. A low SRMR value suggests minimal discrepancy between the observed and estimated covariance matrices, supporting the adequacy of the proposed model [31]. These findings reinforce the validity of the UTAUT2 model in predicting students' acceptance of ChatGPT.

After conducting these analyses, we proceeded to examine the influence of other variables, such as gender, age, and field of study, on the degree of ChatGPT acceptance.

For all cases, the hypotheses were formulated as follows:

- Null Hypothesis (H_0): There are no significant differences based on gender, with an alpha risk of 0.05 for the different variables tested.
- Alternative Hypothesis (H_1): There are significant differences based on gender, with an alpha risk of 0.05 for the different variables tested.

Starting with the gender variable, and applying the Mann-Whitney U test, we obtained the results presented in Table 7.

Table 7. Significant Differences Based on Students' Gender Across the Different UTAUT Dimensions

	PE	EE	SI	FC	BI	UB
Mann-Whitney U	3982,5	4078,0	3653,0	3977,5	3612,0	3490,0
Wilcoxon W	11732,5	11828,0	11403,0	11727,5	11362,0	11240,0
Z	-,972	-,721	-1,838	-,997	-1,976	-2,326
Sig.	,331	,471	,066	,319	,048(*)	,020(*)

Note: * = significant differences at the 0.05 level.

The results obtained only allow for the rejection of H_0 at a significance level of $p \leq 0.05$ concerning "behavioral intention" and "usage behavior".

To determine which gender these differences favored, a rank test was applied, yielding the values presented in Table 8 for the two accepted alternative hypotheses.

Table 8. Rank Test Between "Behavioral Intention" and "Usage Behavior" Dimensions and Students' Gender.

Dimension	Gender	N	Mean Rank	Sum of Ranks
BI (Behavioral Intention)	Male	70	107,90	7553,00
	Female	124	91,63	11362,00
	Total	194		
UB (Usage Behavior)	Male	70	109,64	7675,00
	Female	124	90,65	11240,00

Regarding age, the Kruskal-Wallis test was applied, and the results obtained are presented in Table 9.

Table 9. Significant Differences Based on Students' Age Across the Different UTAUT Dimensions.

	PE	EE	SI	FC	BI	UB
Kruskal-Wallis H	1,826	11,092	7,760	6,437	9,552	11,126
df	4	4	4	4	4	4
Sig.	,768	,026(*)	,101	,169	,049(*)	,025(*)
Kruskal-Wallis H	PE	EE	SI	FC	BI	UB

Note: * = significant differences at the 0.05 level.

In this case, the H_0 hypotheses rejected at $p \leq 0.05$ were those related to the nonexistence of significant differences concerning age and the following UTAUT2 dimensions: "Usage Behavior," "Behavioral Intention," and "Effort Expectancy."

In Table 10, the differences in the rejected hypothesis are presented, indicating which age group the differences favored. To determine this, the rank test was applied again.

Table 10. Rank Test Between "Usage Behavior," "Behavioral Intention," and "Effort Expectancy" Dimensions and Students' Age

	Age Group	N	Mean Rank
EE (Effort Expectancy)	18-20 years	57	96,65
	21-30 years	99	106,37
	31-40 years	21	63,62
	41-50 years	8	90,94

	Over 50 years	9	90,22
	Total	194	
BI (Behavioral Intention)	18-20 years	57	84,88
	21-30 years	99	104,93
	31-40 years	21	79,74
	41-50 years	8	114,06
	Over 50 years	9	122,44
	Total	194	
UB (Usage Behavior)	18-20 years	57	91,21
	21-30 years	99	107,09
	31-40 years	21	76,26
	41-50 years	8	61,81
	Over 50 years	9	113,11
	Total	194	

The results indicate that, in general, students aged 21-30 years exhibited the highest acceptance of the technology analyzed in this study.

Finally, we tested H_0, referring to the existence or absence of significant differences across the various UTAUT2 dimensions based on the students' field of study. The Kruskal-Wallis values presented in Table 11 indicate that none of the H_0 hypotheses can be rejected at $p \leq 0.05$. Consequently, we can conclude that there are no significant differences between the various UTAUT dimensions regarding the acceptance of ChatGPT and the students' field of study.

Table 11. Kruskal-Wallis Test Results for Field of Study.

	PE	**EE**	**SI**	**FC**	**BI**
Kruskal-Wallis H	11,995	10,285	12,486	10,609	7,385
df	6	6	6	6	6
Sig.	,062	,113	,052	,101	,287

5. Conclusions, Research Limitations, and Future Research Directions

This study has systematically addressed the degree of acceptance of ChatGPT among Costa Rican university students, using the UTAUT2 (Unified Theory of Acceptance and Use of Technology) model as a theoretical framework. The findings point in different directions:

The first key aspect relates to the validity and reliability of the instrument used to analyze students' acceptance of ChatGPT.

Additionally, the model has been validated, indicating that dimensions such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention are key factors in determining students' usage behavior of this AI-based tool. In particular, it has been observed that students who use ChatGPT more frequently tend to perceive it as a useful and easy-to-use tool, highlighting the need for its effective integration into educational environments.

The findings of this study align with previous research conducted by [32, 33, 34, 35, 28, 36, 37], suggesting that the UTAUT2 model is well-established as a robust theoretical framework for understanding technological acceptance in the educational field. These results reinforce the importance of continuing to explore the factors that influence students' willingness to adopt AI technologies in their learning processes.

The incorporation of AI-based tools, such as ChatGPT, in higher education presents a set of challenges for both teachers and students. Both groups must adapt to a dynamic teaching-learning ecosystem, which requires continuous updates in their knowledge and digital skills. Digital literacy thus becomes a fundamental component in ensuring an effective adaptation to these new scenarios. In this context, [16] found that a significant proportion of students use AI tools at least once a week, suggesting a positive inclination toward their integration into academic practices.

Additionally, this study has highlighted that the degree of acceptance of ChatGPT is influenced by students' gender and age. Men show greater interest in this technology, and the age group of 21-30 years exhibits the highest level of acceptance.

This study provides a valuable contribution from both a scientific and social perspective, offering a deeper understanding of AI acceptance in education. Its findings can serve as a foundation for future research aimed at examining in greater detail the interaction between technology and learning. Additionally, it provides useful insights for educational institutions and academic policymakers, facilitating evidence-based decision-making regarding the implementation of training programs and the development of technological resources.

Despite its contributions, this study has some limitations that should be considered for a comprehensive understanding of the results:

- Sampling Method: The study employed a convenience sampling method, which presents certain disadvantages compared to random sampling [38]. Future research should replicate this study using a random selection of participants.
- Self-Reported Data: The data collection instrument relied on self-reports, which have inherent limitations [39]. However, as Yousafzai, Foxall & Pallister [40] point out, obtaining objective measures of technology acceptance is challenging, unless the technology is used consistently.
- Ex-Post-Facto Design: The ex-post-facto methodological design prevents the establishment of causal relationships between the analyzed variables.

Future Research Directions

Training in AI-based tools is a key factor in the technology adoption process. This is not only because AI is transforming teaching and learning methods, but also due to its broader social and cultural implications. Chang et al. [41] emphasize that students' ability to use ChatGPT significantly influences their acceptance of the tool, reinforcing the need to provide appropriate training programs to enhance its pedagogical use. In this sense, the AI revolution extends beyond technology, becoming a phenomenon that redefines interactions with knowledge and education.

Ultimately, the real challenge is not just learning to use these tools, as this process will naturally occur over time. The crucial aspect is to understand and manage the structural changes that AI will introduce in society and education, as well as the ideological values underlying its implementation [42]. This perspective invites a critical reflection on AI’s impact, not only in the academic field but also within the sociocultural framework in which it operates.

Therefore, future research should expand the scope of this study to other fields of knowledge and educational levels, aiming to achieve a more holistic understanding of ChatGPT acceptance. Additionally, it would be pertinent to analyze the long-term impact of AI use on academic performance and the development of students' digital competencies.

A mixed-method approach, combining qualitative and quantitative techniques, would allow for a deeper understanding of students’ perceptions and attitudes toward AI in education. Moreover, as suggested by Tamilmani, Rana, Wamba & Dwivedi [33] in their meta-analysis on UTAUT2 and AI research, it is crucial to consider contextual variables to better understand technology adoption levels, which would necessitate replicating this study.

6. Patents

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