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Latent dimensions in the adoption of ChatGPT at the University: CHASSIS model

Dimensiones latentes en la adopción de ChatGPT en la universidad: modelo CHASSIS

Dra. Luz Marina Pereira-González is a research professor at Universidad Técnica del Norte, Grupo de Investigación de Ciencias en Red (eCIER), (Ecuador) (lmpereira@utn.edu.ec) (https://orcid.org/0000-0002-7796-9819)

Dra. Andrea Basantes-Andrade is a research professor at Universidad Técnica del Norte, Grupo de Investigación de Ciencias en Red (eCIER), (Ecuador) (avbasantes@utn.edu.ec) (https://orcid.org/0000-0003-1045-2126)

Milton Mora-Grijalva is a lecturer at Universidad Técnica del Norte (Ecuador) (mmmora@utn.edu.ec) (https://orcid.org/0000-0001-7362-1164)

Anabela Galárraga-Andrade is a professor at Universidad Técnica del Norte (Ecuador) (asgalarraga@utn.edu.ec) (https://orcid.org/0000-0002-2323-1253)

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Abstract

The key dimensions influencing the use of *ChatGPT* among university students are analyzed, a topic driven by the growing expansion of generative artificial intelligence across all domains. Based on a two-stage probabilistic sampling method, a questionnaire was administered to 509 students from the Faculty of Education, Science, and Technology at a public university in Ecuador. The instrument integrates well-established theories of technology adoption and includes the adaptation of relevant factors for the use of *ChatGPT* in educational contexts. Through Exploratory Factor Analysis, seven factors were extracted: ethical and academic concerns (PEA), performance expectancy (ED), cost and financial accessibility (CAF), intention to use (IU), social influence/social anxiety (IAS), perceived credibility and reliability (CFP), and facilitating conditions (CF). The latent variables explain 68.6 % of the variance and show high internal consistency (Cronbach's alpha ranging from 0.859 to 0.945), which confers strong reliability to the instrument. The main factor, PEA, highlights the relevance of academic integrity and authorship, while ED and CF underscore the importance of academic effectiveness and institutional support. The proposed model, CHASSIS, contributes to a deeper understanding of the elements influencing the intention to use *ChatGPT*, providing a theoretical foundation for future research.

Keywords: *ChatGPT*, artificial intelligence, exploratory factor analysis, behavioral intention to use, latent variables, higher education.

Resumen

Se analizan las dimensiones determinantes del uso de ChatGPT entre estudiantes universitarios, tema impulsado por la creciente expansión que ha tenido el uso de las inteligencias artificiales generativas en todos los ámbitos. Sobre la base de un muestreo probabilístico bietápico, se aplicó un cuestionario a 509 estudiantes de la Facultad de Educación, Ciencia y Tecnología de una universidad pública de Ecuador, en el que se integran teorías consolidadas de la adopción de tecnologías e incluye la adaptación de factores pertinentes al uso de ChatGPT en contextos formativos. Aplicando un Análisis Factorial Exploratorio, se extrajeron siete factores: preocupaciones éticas y académicas (PEA), expectativa de desempeño (ED), costo y accesibilidad financiera (CAF) intención de uso (IU), influencia/ansiedad social (IAS), confiabilidad y fiabilidad percibidas (CFP) y condiciones facilitadoras (CF). Las variables latentes tienen un poder explicativo del 68,6 % de la varianza y presentan índices altos de consistencia interna (alfa de Cronbach de 0.859 a 0.945) lo cual confiere alta fiabilidad al instrumento. Como factor principal destaca (PEA), poniendo en evidencia la relevancia de la integridad académica y la autoría; mientras que ED y CF revelan la importancia de la eficacia académica y el apoyo institucional. El modelo propuesto, CHASSIS, contribuye a una mejor comprensión de los elementos que influyen en la intención de uso de ChatGPT constituyendo una base teórica para futuras investigaciones.

Palabras clave: *ChatGPT*, inteligencia artificial, análisis factorial exploratorio, intención de uso, variables latentes, educación superior.

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1. Introduction

ChatGPT has evolved significantly in natural language processing. Initially based on GPT models that used statistical patterns to generate text (Roumeliotis and Tselikas, 2023), it has incorporated fine-tuning techniques and human *feedback* to provide more consistent and accurate responses (Latif and Zhai, 2024; Ray, 2023). This evolution is due to improvements in neural network architectures and the use of large volume of data, allowing it to adapt to diverse contexts. GPT-3 relied on a deep learning architecture with approximately 175 billion adjustable parameters (Gupta et al., 2023), which allows it to capture complex language nuances and significantly improve text generation and comprehension.

Among the advantages that differentiate *ChatGPT* from other generative artificial intelligences are its ability to sustain two-way communication, its intuitive interface, and its rapid responsiveness (Gupta, 2024), features that are especially valued in the academia. These qualities facilitate the exploration of ideas, clarification of concepts and assistance in academic writing, critical aspects in the learning process. Furthermore, recent research has evidenced that the use of conversational models such as *ChatGPT* can enhance engagement and efficiency in information search, inclining students' preference towards this tool (Bettayeb et al., 2024; Klimova and de Campos, 2024).

Since its launch, in November 2022, *ChatGPT* experienced an extraordinary expansion, being used by 100 million people in a couple of months (Leng, 2024). This technology has been rapidly adopted in academic environments, although its integration poses challenges that transcend the traditional dimensions of information technologies, requiring an in-depth analysis of its educational and research implications.

Currently, *ChatGPT* characterizes by the diversification of its versions, which include GPT-4, GPT-4o (with synthesized voice), GPT-4o-mini, 4o with programmed tasks (beta), o1 (reasoning model), o3-mini (efficient version of the second reasoning model) and o3-mini-high (optimized for programming and logic). This variety meets the specific needs of increasingly demanding users in various contexts.

In parallel, this rapid evolution requires the development of theories adapted both to the advancement of *ChatGPT* and to its various contexts of use. It is essential to create conceptual models that explain the adoption of this generative artificial intelligence in universities, where teachers and students are increasingly integrated as frequent users.

In this scenario, Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA) provides a solid theoretical framework for understanding behavioral intention in the adoption of *ChatGPT* in university settings. As one of the models with the greatest relevance for predicting people's behavior, TRA establishes that actions are determined by behavioral intention, the direct antecedent of observable behavior (Bosnjak et al., 2020). This intention is shaped by two key components: individual attitudes toward the specific behavior and the perceived subjective norms of the social environment.

The attitudinal component represents the individual's personal evaluation of a specific behavior, based on beliefs about its possible consequences and appraisal of these outcomes (Din Bandhu et al., 2024). Subjective norms, on the other hand, reflect the social pressure that can be perceived to perform or avoid certain behavior, including the expectations of important referents and the motivation to comply with them (Heredia-Carroza et al., 2024). However, ART assumes that the way a person behaves is completely under his or her voluntary control.

To overcome this limitation, Ajzen (1985) developed the Theory of Planned Behavior (TPB), adding a third factor: perceived behavioral control, which represents how the individual perceives the ease or difficulty of performing the behavior. In the educational setting, the TRA explains how the positive attitudes towards tools such as *ChatGPT*, together with the perception of social approval, increase the probability of use, as long as there is control over their access.

The Technology Acceptance Model (TAM) proposed by Davis (1989) is based on two dimensions: perceived usefulness - belief that the technology will improve performance - and perceived ease of use - degree to which adapting to the technology will not present an obstacle.

Venkatesh and Davis (2000) extended this model with TAM2, incorporating Social Influence - impact of beliefs and expectations of significant others - and Instrumental Cognitive Processes - rational evaluations of system characteristics and performance that determine its contribution to job or personal performance.

As additional background, the UTAUT model by Venkatesh et al. (2003) integrates eight previous models to explain the intention and actual use of technological systems through four dimensions: performance expectancy -conviction that the technology will increase efficiency-, effort expectancy -perception of ease of use, social influence -social pressure or support- and facilitating conditions -resources and circumstances that facilitate technological adoption. Subsequently, Venkatesh et al. (2012) extended this theoretical framework with the UTAUT2 model, incorporating additional constructs that better capture the dynamics of acceptance in consumer contexts: hedonic motivation -conceptualized as the enjoyment or personal satisfaction produced by the use of the technology-, price/value -which represents the evaluation of the cost of the technology in relation to the benefits it provides- and habit, which is identified with the tendency to use the technology automatically, based on previous experience. In both models (UTAUT and UTAUT2), intention to use is considered the dependent variable.

In the context of *ChatGPT*, Sallam et al. (2023) propose the *TAME-ChatGPT*, «Technology Acceptance Model Edited to Assess *ChatGPT* Adoption», based on Davis' (1989) TAM. This includes: perceived risk -probability of negative consequences such as privacy problems-, perceived usefulness -consistent with TAM- and social influence, consistent with TAM2 and UTAUT.

Menon and Shilpa (2023) corroborated the UTAUT model factors, adding perceived interactivity-the ability of the system to facilitate two-way communication with adaptive responses-and privacy concerns, similar to perceived risk.

Social influence also appears in studies by Bilquise et al. (2023) and Abdaljaleel et al. (2024), which also consider performance expectancy (or perceived usefulness). The former propose a conceptual model based on TAM and UTAUT.

Bolivar-Cruz and Verano-Tacoronte (2025) found that perceived usefulness and facilitating conditions are common determinants in both sexes.

Choudhury and Shamszare (2023) conducted research showing that trust-understood as credibility in the accuracy, truthfulness, and reliability of the information provided by ChatGPT- determines intention to use. Similarly, Shahzad et al. (2024) include perceived trust as a moderator between ease of use, usefulness, and perceived intelligence.

Romero-Rodriguez et al. (2023) found that experience, performance expectancy, hedonic motivation, price/value, and habit directly influence intention to use *ChatGPT*, while Strzelecki (2024) found that habit, performance expectancy, and hedonic motivation were the determining variables.

Almogren et al. (2024), using structural modeling analysis (SEM), corroborated that perceived ease of use and attitude toward technology predict behavioral intention to use *ChatGPT*.

In their study on the acceptance of *ChatGPT* in university students of social sciences, García-Alonso et al. (2024) found that the latent variables determining intention to use were: perceived usefulness and credibility; in contrast, social impact was not relevant. These factors are integrated in the model proposed by the authors to jointly explain the adoption of *ChatGPT* in the academic environment.

Finally, Surya Bahadur et al. (2024), using PLS-SEM, evidenced that habit, learning value (a concept assimilable to perceived usefulness in the context of academic skills) and social influence exert a positive influence on the intention to use *ChatGPT*, while other latent variables-such as hedonic motivation, effort expectancy, facilitating conditions or performance expectancy- showed no significant effects in their study.

It is important to note that although these models have been important to understanding technological adoption in general, it is necessary to adapt them by reviewing latent variables to specifically address the use of generative AI in higher education in the Latin American context. The emergence of *ChatGPT* as a tool in university environments cannot be understood solely from a functional or instrumental logic, but as part of a broader cultural ecosystem marked by cyberculture, where educational practices, links to knowledge and notions of authorship are profoundly transformed (Vieira Neto and Rocha Bruno, 2025).

In this sense, the purpose of this research was to propose, based on an Exploratory Factor Analysis, a model contextualized to the academic environment, starting from the conceptual basis of

UTAUT+UTAUT2, which explains the expectations of *ChatGPT* use for academic purposes in students of the Faculty of Education, Science and Technology of a public university in Ecuador.

In response to the rapid expansion of generative artificial intelligence and its use among higher education students, specifically in Latin American contexts, this research proposes the CHASSIS model (CHatGPT Adoption and Sustained use among Students in Institutional Settings), a conceptual model that integrates foundations of theories of adoption of the use of TAM, TPB and UTAUT/UTAUT2 technologies, adapted to the phenomenon of *ChatGPT* use that is emerging with great force in educational contexts. Applying an Exploratory Factor Analysis to a probabilistic, stratified, two-stage, stratified sample, seven determinant dimensions were identified that explain the intention to use *ChatGPT* by university students: ethical and academic concerns (EAC), performance expectation (PE), cost and affordability (CFA), intention to use (IU), social influence/anxiety (SIA), perceived reliability and trustworthiness (PCR), and facilitating conditions (FC). These latent variables, in addition to including the main classical dimensions of technology acceptance theories, incorporate components relevant to the contemporary higher education system, such as authorship, perceived risk and institutional support.

The proposed model, CHASSIS, also stands out because by capturing the complexities of students' intention to use *ChatGPT*, it integrates, on the one hand, the motivational elements and, on the other, the contextual barriers that may shape its adoption in this specific population. CHASSIS has a structure that has been empirically validated and adapted to the characteristics of the Ecuadorian university environment. It has an explanatory power of 68.6% of the variance and exhibits high internal consistency indexes in all its factors ($\alpha > 0.85$), this model represents a solid theoretical contribution for future research that seeks to understand and promote an ethical, efficient and sustained use of *ChatGPT* in higher education.

2. Methodology

The approach of this research is quantitative with an exploratory scope, since the objective of the statistical technique employed - exploratory factor analysis - is to identify underlying patterns, i.e., to discover factors that allow us to interpret the structure of relationships between variables, without establishing definitive causal relationships. The target population consisted of 2955 students enrolled in the period October 2024-February 2025, in the Faculty of Education, Science and Technology of a public university in Ecuador.

To obtain the sample size, the formula corresponding to a finite population with categorical variable (1) was used, considering p = q = 0.5, which represents the most unfavorable condition. A Z value equal to 1.96 was considered, which corresponds to a significance level of 5% and a sampling error, e, of 5%.

$$n = \frac{Z^2 pqN}{e^2(N-1)+Z^2 pq} \qquad (1)$$

The minimum sample size required was 341 and, for practical purposes of applying the instrument, a final sample size of 509 students was used.

A two-stage stratified probability sampling was used, with items selected using SPSS 29.0.2.0, based on the data of students enrolled in the 13 careers of the faculty. In the first stage, the careers were considered as strata and the semesters as clusters, assigning unit weight to all the elements. Simple random sampling without replacement was applied, considering proportional values according to the number of students per course. In the second stage, we stratified by sex using simple random sampling without replacement, with values adjusted according to the proportions by career, level and sex. After selecting the sample, the questionnaire was administered to students who provided written informed consent. The participants were informed about the academic use of the data for publication of the results, guaranteeing their anonymity and confidentiality in the handling of the information.

Table 1 shows the ages of the students in the sample by career and gender.

The technique used in the research was the survey, and the instrument was the questionnaire, with closed and open questions, the latter to obtain informed consent in which the name of the student (subsequently anonymized), sector, city and province of residence were requested. In order to better understand the context of the application, they were asked about their nationality, ethnic self-recognition and grade point average. The questionnaire was placed online in Microsoft Office 360. Two surveyors were designed for each level of each career, who, in person, explained to the students the objectives and scope of the project, provided additional information on the anonymous treatment of the data and gave general instructions for filling out the form.

Based on the previous review of theories and models found in the background, a strategy matrix was constructed for elaborating the questionnaire, which was validated by two experts. Subsequently, a pilot test was conducted with 30 volunteer students from the Faculty and the refined instrument was applied to cover the eight factors of interest in the study: 1) Perceived Academic Usefulness and Effectiveness (expectation of performance or achievement), PE; 2) Hedonic Motivation, MH; 3) Social Influence/Anxiety, SIA; 4) Cost and affordability, CFA; 5) Facilitating Conditions (institutional support and technological competencies), FC; 6) Intention to use (behavioral intention to use, referring to the propensity to act, i.e., to continue using the tool), IU; 7) Ethical and academic concerns, EAC; 8) Perceived reliability and trustworthiness, PCR. Both Kaiser's (1960) criteria and the sedimentation plot were used to select the number of factors.

Table 1. *Descriptive statistics of the age of the students in the sample by career and gender*

			Age			
Career	**Women**	**Men**	**Minimum**	**Maximum**	**Mean**	**Standard deviation**
Fine Arts	17	10	19	30	21.52	2.39
Communication	21	17	18	27	21.39	2.07
Graphic Design	14	23	18	26	20.86	2.03
Basic Education	35	9	18	29	21.32	1.99
Initial Education	40	3	19	28	21.47	1.94
Sports Training	8	30	18	35	22.03	3.15
Physical Activity and Sport Pedagogy	10	31	18	33	21.27	2.65
Arts and Humanities Pedagogy	22	11	18	33	22.06	2.77
Pedagogy of Experimental Sciences	19	17	18	31	21.22	2.49
Pedagogy of national and foreign languages	33	12	18	31	21.31	2.33
Psychology	33	13	18	29	21.15	2.40
Psychopedagogy	38	9	19	33	21.47	2.67
Advertising	15	19	19	38	22.09	3.31
	509					

It was decided to use the Kaiser criterion to determine how many factors should be extracted in the exploratory factor analysis because it is a method widely recognized for its effectiveness and frequent use in psychometric and educational research. According to this criterion, only those factors whose eigenvalue is greater than 1.0 are retained, which implies that the factors involved are capable of explaining more variance than an individual variable. The exploratory nature of the study means that it is aimed at discovering a clear latent structure that will serve as a basis for future confirmatory validations. Although there are other approaches to determine the number of factors to extract in an exploratory factor analysis, such as parallel analysis or Velicer's MAP test, Kaiser's criterion provided results that were entirely consistent with the sedimentation plot, reaffirming the validity of the seven factors identified. Moreover, considering the high sample adequacy (KMO = 0.939) and the significant number of variables analyzed, the number of factors extracted on the basis of the Kaiser criterion made it possible to avoid the inclusion of factors of little relevance and ensure a solid and parsimonious CHASSIS model.

In this first product of the research, the sample data were treated with the technique for dimension reduction of the Exploratory Factor Analysis, EFA. The software used for the study of assumptions and exploratory factor analysis was JASP 0.19.3.

3. Results

The purpose of the instrument applied in this study was to find an appropriate model, adapted to the context of *ChatGPT* use in universities, based on previous theories that were proposed for research on the use of technology. Therefore, the name proposed for this model is «Adoption and Sustained usage of *ChatGPT* among Students in Institutional Settings», CHASSIS (CHatGPT Adoption and Sustained usage among Students in Institutional Settings).

The AFE application in the model showed that the hedonic motivation factor (Venkatesh et al., 2012; Romero-Rodríguez et al., 2023; Strzelecki, 2024) was not present among university students, being finally constituted by the other seven factors.

The review of previous assumptions as to whether there was sufficient correlation between the items was established through Bartlett's test of sphericity (1951) and the Kaiser-Meyer Olkin test (KMO), Kaiser (1970). The test of sphericity evaluates the null hypothesis that the correlation matrix is an identity matrix. The result of Bartlett's test of sphericity was significant, suggesting that the data present sufficient correlations to perform a factor analysis. The Kaiser-Meyer-Olkin sampling adequacy index (KMO) was 0.939, with individual values ranging from 0.902 to 0.960, confirming the suitability of the data for factor analysis (Kaiser, 1974).

The results of Cronbach's alpha (1951) indicated internal consistency levels ranging from 0.859 to 0.945, evidencing a high reliability of the scales used (Table 2).

Table 3 shows the eigenvalues and variance explained in the unrotated and rotated solution of the exploratory factor analysis. It can be seen that with the seven factors extracted, 68.6% of the variance is explained.

Table 4 shows the matrix of factor loadings for the CHASSIS model. The loadings on other factors have been intentionally suppressed for a better visualization of the behavior, but it is important to note that the factor loadings show a well-defined structure, with each item loading predominantly on a single factor. Loadings on other factors are less than 0.18, indicating low collinearity and minimizing the risk of factor overlap. This suggests that the extracted factors are clearly distinguishable and that each item contributes specifically to its respective construct. Furthermore, the low magnitude of the cross-loadings (< 0.18) indicates that the items do not present ambiguity in their association with the factors, which reinforces the discriminant validity of the factor model obtained..

Table 2. *Cronbach's alpha results and 95% confidence intervals for the factors evaluated*

		Interval of confidence interval 95 %		
Factor	Alpha of Cronbach's Factor	Error standard error	Limit lower limit	Limit upper limit
Ethical and Academic Concerns (EAC)	0.939	0.06	0.928	0.95
Expectation of performance (PE)	0.930	0.05	0.921	0.94
Cost and affordability (CFA)	0.928	0.007	0.913	0.942
Intention to use (IU)	0.912	0.010	0.892	0.932
Influence/social anxiety (SIA)	0.859	0.014	0.832	0.886
Perceived reliability and trustworthiness (PCR)	0.904	0.012	0.880	0.928
Facilitating conditions (FC)	0.889	0.014	0.862	0.917
Total	0.945	0.006	0.933	0.957

Table 3. *Eigenvalues and explained variance in the unrotated and rotated solution of the exploratory factor analysis*

		Untotated solution			Rotated solution		
Factor	Eigenvalue	Sum of loads to squared	Ratio of variance	Cumulative	Sum of loads to squared	Ratio of variance	Cumulative
EAC	12.539	12.229	0.340	0.340	5.847	0.162	0.162
PE	4.549	4.243	0.118	0.458	4.782	0.133	0.295
CFA	4.174	3.858	0.107	0.565	4.167	0.116	0.411
IU	1.649	1.369	0.038	0.603	2.890	0.080	0.491
SIA	1.486	1.177	0.033	0.635	2.466	0.069	0.560
PCR	1.234	0.961	0.027	0.662	2.307	0.064	0.624
FC	1.128	0.855	0.024	0.686	2.235	0.062	0.686

In Table 4, the uniqueness column represents the proportion of the variance of each item that is not explained by the common factors. The uniqueness values obtained in the factor analysis reflect that most of the items are well represented by the extracted factors, with values below 0.40. However, some items present higher values (≥ 0.45), suggesting a higher specific variance not explained by the common factors. These items could be analyzed in terms of their wording, conceptual relevance or even their relationship with other items in order to determine whether their integration into the model is adequate or whether they require adjustments. Nevertheless, in general terms, the factor structure shows an adequate representation of the items, with a distribution of variance that supports the validity of the model.

Finally, Table 5 presents the matrix of factorial correlations.

Table 4. *Matrix of factor loadings of the CHASSIS model*

	F1_F1_EAC	F2_PE	F3_CFA	F4_IU	F5_SIA	F6_PCR	F7_FC	Uniqueness
EAC_I1	0.957							0.211
EAC _I2	0.924							0.270
EAC _I3	0.896							0.284
EAC _I4	0.888							0.242
EAC _I5	0.812							0.338
EAC _I6	0.810							0.327
EAC _I7	0.675							0.466
EAC _I8	0.619							0.442
EAC _I9	0.549							0.549
PE_I1		0.897						0.277
PE _I2		0.893						0.269
PE _I3		0.869						0.292
PE _I4		0.835						0.357
PE _I5		0.732						0.367
PE _I6		0.720						0.389
PE _I7		0.661						0.354
CFA_I1			0.924					0.238
CFA _I2			0.918					0.211
CFA _I3			0.798					0.311
CFA _I4			0.784					0.311

	F1_F1_EAC	F2_PE	F3_CFA	F4_IU	F5_SIA	F6_PCR	F7_FC	Uniqueness
CFA _I5			0.779					0.319
CFA _I6			0.701					0.414
IU_I1				0.885				0.223
IU_I2				0.841				0.238
IU_I3				0.827				0.251
IU_I4				0.712				0.348
SIA_I1					0.871			0.258
SIA _I2					0.779			0.418
SIA _I3					0.767			0.370
SIA _I4					0.650			0.459
PCR_I1						0.860		0.226
PCR _I2						0.854		0.208
PCR _I3						0.850		0.280
FC_I1							0.892	0.230
FC_I2							0.834	0.258
FC_I3							0.786	0.302

Table 5. *Matrix of factorial correlations*

FACTOR	EAC	PE	CFA	IU	SIA	PCR	FC
EAC	1.000	0.304	0.299	0.521	0.372	0.237	0.260
PE	0.304	1.000	0.346	0.644	0.192	0.558	0.355
CFA	0.299	0.346	1.000	0.376	0.603	0.463	0.554
IU	0.521	0.644	0.376	1.000	0.267	0.510	0.402
SIA	0.372	0.192	0.603	0.267	1.000	0.373	0.401
PCR	0.237	0.558	0.463	0.510	0.373	1.000	0.525
FC	0.260	0.355	0.554	0.402	0.401	0.525	1.000

4. Discussion and conclusions

The Cronbach's alpha values (1951) obtained in Table 2 indicate that the items that make up each factor present high internal consistency, which supports the reliability of the scales that have been used in the measurement of the constructs, and even the factor with the lowest value (Social influence/anxiety, 0.859) is in an acceptable and robust range for research purposes (Tavakol and Dennick, 2011). Although very high values may indicate redundancy among the items, in this case, when analyzing the subdomains or factors individually, it is observed that each one provides specific information on differentiated theoretical dimensions.

Regarding the percentage of variance explained (Table 3), the first factor (EAC) concentrates a very high eigenvalue (12.539), explaining about 34% of the variance. This is usual in unrotated solutions, where the first factor tends to absorb a large part of the shared variance due to the lack of fit in the structure. With oblique rotation, a more balanced distribution of variance among the factors is observed. The results of the percentage of variance explained in the unrotated and rotated solutions confirm the presence of a complex factor structure and reinforce the usefulness of applying rotation to obtain a more interpretable solution. Table 5 about correlations between factors confirms the selection adequacy of the oblique rotation with the promax method (Akhtar-Danesh, 2023), since it was found that the factors are not completely independent, for example, between factors 2 and 4 and between 3 and 5, there are correlations higher than 0.6, which are tolerated by the promax method. In the field of social sciences, factor solutions that explain around 50 %-60 % of the total variance are usually considered acceptable (Hair et al., 2019). In this case, reaching almost 69 % is evidence of a robust structure.

In the factor analysis conducted in this research, it has been possible to establish the relevance of seven factors related to the intention to use *ChatGPT* in an institutional setting. Most of the items present high loadings, above 0.70, indicating a strong association between each item and its factor (Hair et al., 2019). A clear distribution of items is observed: each item is grouped in a specific factor without relevant cross-loadings (no loadings above 0.18), suggesting good convergent validity (Brown, 2015). In general, Table 4 shows that most of the items have a moderate-low uniqueness, which confirms that each factor explains a relevant part of the variance of its items.

The results are consistent with a hybrid model of preceding theories related to both Reasoned Action and Planned behavior (TRA and TBP) and the Technology Acceptance Model (TAM) and the unified theories of acceptance and use of technologies in original and extended version (UTAUT, UTAUT2); but it has its own traits of using a generative artificial intelligence, specifically in a university context.

Of the seven factors, the one that contributes most to explaining the variance is that of ethical and academic concerns, EAC, which can be explained as the perceived risk in relation to the development of critical thinking, authorship, originality, unintentional plagiarism, adequate recognition of the tool's contribution, and the importance of questioning ethical aspects. High loadings indicate that these items consistently describe aspects such as concern about fraud or academic dishonesty. The item with the lowest loading (0.549) is still relevant, pointing to small fears associated with ethical aspects in the use of the tool. This result is in line with the studies of Sallam et al. (2023), Menon and Shilpa (2023), Farhi et al. (2023), Abdaljaleel et al. (2024) and Stahl and Eke (2024), who found that the use of *ChatGPT*, in university students, raises concerns and worries about authorship, integrity and ethics.

The second factor obtained is related to the expectation of performance, PE. This is the factor most frequently considered in technology use models (UTAUT, TAM). It was found that students perceive that using *ChatGPT* has a positive impact on academic performance and makes them more efficient, mainly because of the resources it provides that facilitate learning and understanding of academic subjects, so they are satisfied with the experience. The high loadings indicate that students positively value the improvement in the quality of their assignments and that the use of *ChatGPT* allows them to quickly obtain good results;, but they are slightly less satisfied with the overall experience (0.661). This result is consistent with the studies of Davis (1989), Venkatesh and Davis (2000), Venkatesh et al. (2003), Bilquise et al. (2023), Sallam et al. (2023), Abdaljaleel et al. (2024), Garcia-Alonso et al. (2024), Bolivar-Cruz and Verano-Tacoronte (2025), Firat and Kuleli (2025), Romero-Rodriguez et al. (2023), Menon and Shilpa (2023), Strzelecki (2024), Surya Bahadur et al. (2024) and Shahzad et al. (2024).

The third factor found was cost and affordability, CFA, which is considered by Venkatesh et al. (2012) in UTAUT2, and relates to the impact that lack of resources may have on the use of *ChatGPT*. Given that the range of loadings is high (mostly above 0.78), it is perceived that the dimension of «financial accessibility» is very present and that respondents consistently rate whether *ChatGPT* use entails financial barriers or constraints. Significant effects of this factor were also found in the work of Romero-Rodriguez et al. (2023) and Abdaljaleel et al. (2024).

The fourth factor corresponded to intention to use, IU, included in TAM and congruent with the studies of Venkatesh et al. (2003), Venkatesh et al. (2012), Bilquise et al. (2023) and Strzelecki (2024). High loadings indicate that participants who score high on these items have a clear willingness to employ the tool for their studies or research.

The fifth factor relates to social influence/anxiety, SIA, and relates to the use of *ChatGPT* causing some nervousness, stress or anxiety and to the influence of peer opinion on the decision to use. The social influence factor has also been found to be relevant in research by Bilquise et al. (2023), Choudhury and Shamszare (2023), Shahzad et al. (2024), and Garcia-Alonso et al. (2024). In this study, no negative influence was found between the presence of anxiety and intention to use *ChatGPT*. Budhathoki et al. (2024) also studied the influence of anxiety in the UK and Nepal, finding a negative effect on intention to use behavior in the UK, but not on use behavior; while in Nepal it had no effect on intention to use.

The sixth factor was Perceived reliability and trustworthiness (PCR) in which a positive perception was found in relation to the accuracy and reliability of the responses issued by *ChatGPT*. This factor is considered by Bilquise et al. (2023), Choudhury and Shamszare (2023), Shahzad et al. (2024), Garcia-Alonso et al. (2024), and Lai et al. (2024). High loadings suggest that participants clearly distinguish this factor and tend to agree that *ChatGPT* provides them with reliable answers.

Finally, the seventh factor was constituted by the facilitating conditions (FC) in which students expressed their perception that the institution facilitates access and support to use generative artificial intelligence tools. This result is in agreement with the UTAUT model (Venkatesh et al., 2003), Menon and Shilpa (2023) and Bolivar-Cruz and Verano-Tacoronte (2025).

The CHASSIS model constitutes a contextualized proposal to analyze *ChatGPT* adoption in the university setting by integrating relevant factors from previous theories (UTAUT, TAM, TPB, TAR) and adapting them to the use of a generative AI. Among its contributions, the identification of ethical and academic concerns as the main factor explaining variance stands out, evidencing the importance of addressing issues such as authorship, integrity and originality in this context, this factor being crucial in the case of socio-educational research (Pastor-Andrés et al., 2025). In addition, the scale shows high levels of internal consistency in most of the factors, which reinforces its reliability. Nevertheless, the findings should be interpreted with caution, since the fact that the study is cross-sectional limits the possibility of inferring causal relationships and, given the specificity of the setting analyzed, generalization to other universities or regions could require additional adaptations.

The adoption of *ChatGPT* depends not only on the expectation of performance and intention to use it, but also on trust in the tool and the presence of facilitating conditions promoted by the institution. The strong correlation between certain factors suggests that institutional support and perceived trustworthiness may enhance responsible use, but at the same time social influence/anxiety and cost may act as barriers. For future studies, it is recommended to (a) perform confirmatory validations and longitudinal analyses that explore how perceptions and behaviors evolve, (b) contrast this model with other AI technologies, and (c) delve into the incidence of cultural and normative aspects in different university contexts.

In conclusion, the CHASSIS model offers a robust and relevant framework for understanding the dimensions that influence the acceptance of *ChatGPT* in an academic environment, confirming the relevance of ethical and academic factors, performance, trustworthiness, social influence, financial and institutional support. The high internal consistency indices (0.859-0.939), the high percentage of variance explained, 68.6 %, and the clear differentiation of the constructs highlight their potential for guiding interventions that seek to promote ethical and efficient use of generative AI. Although further studies will be required to corroborate these findings and analyze their applicability in diverse contexts, the present research establishes a significant starting point for the theoretical and practical development of *ChatGPT* integration in higher education.

Author contributions

Luz Marina Pereira-González: conceptualization, data curation, formal analysis, research, methodology, project management, resources, supervision, validation, visualization, original draft-writing, writing-revision and editing.

Andrea Basantes-Andrade: conceptualization, formal analysis, research, methodology, supervision, validation, original draft-writing, writing-revision and editing.

Milton Mora-Grijalva: conceptualization, research, supervision, validation, writing-revision and editing.

Anabela Galárraga-Andrade: conceptualization, research, supervision, validation, writing-revision and editing.

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