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ORIGINAL

Factors influencing satisfaction and continued use intention of ChatGPT in the academic context: analysis using structural equation modeling

Factores que influyen en la satisfacción y la intención de uso continuado de ChatGPT en el contexto académico: análisis mediante modelos de ecuaciones estructurales

Edgar Rolando Morales Caluña[1], Dario Javier Cervantes Diaz[2], Cristian Ismael Morales Caluña[3], Fernando Xavier Altamirano Capelo[4]

[1]Universidad Estatal de Milagro, Carrera de Nutrición y Dietética. Milagro, Ecuador.
[2]Universidad Estatal de Milagro, Carrera de Derecho. Milagro, Ecuador.
[3]Universidad Técnica de Ambato, Dirección de Técnologias de la Información. Ambato, Ecuador.
[4]Escuela Superior Politécnica de Chimborazo, Carrera de Promoción y Cuidados de la Salud. Ecuador.

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Corresponding author: Edgar Rolando Morales Caluña

ABSTRACT

Artificial intelligence tools like ChatGPT have transformed higher education by facilitating academic tasks and improving autonomous learning. However, their acceptance and continued use depend on factors such as compatibility, efficiency, satisfaction, and intention to use. This study applies Structural Equation Modeling (SEM) to evaluate these relationships. To analyze how these factors influence user satisfaction and continued use intentions of ChatGPT among university students. Study involved 210 students from Ecuadorian universities. Validated surveys were used to assess six constructs: compatibility, efficiency, perceived ease of use, perceived usefulness, satisfaction, and continued use intention. Data were analyzed using Exploratory and Confirmatory Factor Analysis, followed by SEM for model adjustment. The findings identified a four-factor structure explaining 63 % of the variance. Fit indices were acceptable (CFI = 0,876, SRMR = 0,064), with significant factor loadings ($p<0,001$). However, high correlations among factors suggested conceptual redundancy. ChatGPT is perceived as a useful, satisfying tool aligned with students' learning styles, promoting its continued adoption. Nonetheless, refining the factor structure could improve the model.

Keywords: ChatGPT; User Satisfaction; Intention To Use; Higher Education; Artificial Intelligence.

RESUMEN

Las herramientas de inteligencia artificial como ChatGPT han transformado la educación superior al facilitar las tareas académicas y mejorar el aprendizaje autónomo. Sin embargo, su aceptación y uso continuo dependen de factores como la compatibilidad, la eficiencia, la satisfacción y la intención de uso. Este estudio aplica el Modelo de Ecuaciones Estructurales (MEE) para evaluar estas relaciones. El objetivo es analizar cómo estos factores influyen en la satisfacción del usuario y la intención de uso continuo de ChatGPT entre estudiantes universitarios. El estudio incluyó a 210 estudiantes de universidades ecuatorianas. Se utilizaron encuestas validadas para evaluar seis constructos: compatibilidad, eficiencia, facilidad de uso percibida, utilidad percibida, satisfacción e intención de uso continuo. Los datos se analizaron mediante Análisis Factorial Exploratorio y Confirmatorio, seguido del MEE para el ajuste del modelo. Los hallazgos identificaron una estructura de cuatro factores que explica el 63 % de la varianza. Los índices de ajuste

fueron aceptables (CFI = 0,876, SRMR = 0,064), con cargas factoriales significativas (p < 0,001). Sin embargo, las altas correlaciones entre los factores sugirieron redundancia conceptual. ChatGPT se percibe como una herramienta útil y satisfactoria, alineada con los estilos de aprendizaje de los estudiantes, lo que promueve su adopción continua. No obstante, perfeccionar la estructura factorial podría mejorar el modelo.

Palabras clave: ChatGPT, Satisfacción del Usuario; Intención de Uso; Educación Superior; Inteligencia Artificial.

INTRODUCTION

The integration of artificial intelligence (AI)-based technologies has revolutionized the educational domain, particularly within higher education. Among these innovations, ChatGPT, developed by OpenAI, has gained prominence due to its ability to interact naturally with users, providing real-time answers and personalized assistance. However, its acceptance and sustained use in academic environments hinge on several factors, including users' perceptions of its utility and ease of use, as well as considerations related to ethical implications.[1]

User satisfaction is a critical factor in the success of educational tools. For ChatGPT, satisfaction is grounded in the perceived compatibility with diverse learning styles, task efficiency, and ease of adoption. When users perceive that a technological tool aligns with their needs, supports their learning preferences, and simplifies task completion, it fosters a more positive experience, encouraging continued use and recommendations within academic and social circles. Identifying the factors that influence user satisfaction and how they impact the intention to continue using ChatGPT is essential for optimizing its implementation in educational contexts.[2]

The Technology Acceptance Model (TAM) serves as a valuable theoretical framework for analyzing the adoption of technologies like ChatGPT. According to TAM, perceived ease of use and perceived usefulness are key determinants of technology acceptance. However, recent studies have extended the model to include additional relevant variables, such as compatibility and perceived efficiency. In the context of ChatGPT, compatibility refers to how well the tool aligns with students' learning methods, while efficiency focuses on the tool's ability to save time and enhance the quality of outcomes.[3]

Compatibility is a central concept within the diffusion of innovations theory. In the educational context, it pertains to the extent to which ChatGPT aligns with students' learning styles. This perception is significant, as users are more likely to adopt technologies they perceive as consistent with their study methods and needs. Additionally, perceived efficiency is crucial for users managing multiple tasks, as ChatGPT can deliver rapid and accurate responses, streamlining the handling of academic demands.[4]

Perceived ease of use is also fundamental for technology adoption. In the case of ChatGPT, an intuitive interface and the ability to deliver results quickly can encourage more frequent use. This lowers the entry barrier for students, fostering a positive user experience and prolonged engagement with the tool. Additionally, the perceived usefulness of ChatGPT, tied to its capacity to enhance learning and task effectiveness, directly impacts user satisfaction and their willingness to continue using the tool in the future.[5]

The continued use intention of ChatGPT is a crucial aspect of its long-term success in higher education. Beyond initial adoption, continued use relies on the perception that the tool remains relevant and beneficial for users. This intention is shaped by the satisfaction experienced and the belief that ChatGPT will continue to be useful in the future. Understanding how these factors interrelate is essential for promoting the effective adoption of ChatGPT within educational contexts.[6]

This study examines how compatibility, perceived efficiency, ease of use, and usefulness influence user satisfaction and continued use intention of ChatGPT. Through Structural Equation Modeling (SEM), the relationships among these factors are identified and evaluated, enabling a comprehensive understanding of the user experience. The findings of this study provide valuable insights for improving the implementation of ChatGPT in educational settings and promoting more effective use of artificial intelligence in higher education.

The Use of ChatGPT in Higher Education

In the past three years, the use of ChatGPT in higher education has become a topic of growing academic interest. Numerous studies highlight its potential to enhance the learning experience by providing immediate and personalized responses to student queries, facilitating the understanding of complex concepts. Recent research has explored its role as a virtual assistant in academic tasks, demonstrating that ChatGPT can support essay writing, idea generation, and problem-solving. However, challenges have also been identified, such as the risk of dependency and a potential decline in students' critical thinking skills when the tool is used excessively.[7]

Furthermore, the accuracy of responses and the tendency to generate incorrect information have been critical concerns regarding its use in educational contexts. Despite these limitations, most studies agree that ChatGPT holds significant potential to complement traditional teaching, particularly in hybrid or remote

learning models, where its ability to provide constant interaction can be a valuable resource for students. Collectively, these studies suggest that the key to its successful integration in higher education lies in its role as a support tool rather than a substitute for human instruction.[8]

Use of ChatGPT in academic activities among university students

Over the past three years, the use of ChatGPT in academic settings has garnered increasing interest, particularly in the university context. This OpenAI tool has proven to be a valuable resource for supporting students in essay writing, idea generation, and resolving complex queries. Recent research highlights its ability to facilitate the understanding of concepts through detailed explanations tailored to the needs of students, thereby promoting autonomous learning.[9]

Additionally, studies emphasize its usefulness in remote and hybrid education environments, where students often require additional support to manage their learning.[10] However, challenges such as variability in response quality and the risk of fostering excessive dependence on the tool have also been noted. Overall, recent literature suggests that the effectiveness of ChatGPT relies on its proper integration into teaching processes and the role of educators in guiding its ethical and efficient use within the university context.[9]

METHOD

Context of the research

Currently, there are no official statements regarding the use of tools like ChatGPT in universities within the country, and its usage is informally monitored through online platforms. However, students have become accustomed to utilizing various AI tools for activities such as conducting research, writing essays, solving tests, and completing practical assignments. From a personal perspective, the use of these tools by students is evident. This study focused on analyzing students' experiences and perceptions regarding their use of ChatGPT among the participants.

Research participants

The participants in this research were students from Ecuadorian universities who voluntarily and freely completed the survey. The survey (https://docs.google.com/forms/d/e/1FAIpQLSfnoboD0KKdbZnki5DMa7DzZH8wKMKRkJKoXQdqmr4BU5-Miw/viewform) was available from October 17 to November 2, 2024, yielding 210 valid responses, with 75 % of participants identifying as female and 25 % as male. Four students did not complete the survey. Students from seven universities participated, representing seven academic disciplines, including medicine, nutrition, systems engineering, education, and others.

Table 1. Demographic information of the participants

		Female	Male	Total
University	Amawtay Wasi University	24	3	27
	Polytechnic High School Of Chimborazo	41	18	59
	University Of Guayaquil	1		1
	State University Of Miracle	54	5	59
	National University Of Chimborazo	22	20	42
	National University Of Education	2	1	3
	Technical University Of Cotopaxi	13	6	19
Race	Economics	1		1
	Basic Education	2		2
	Agro-Industrial Engineering	10	6	16
	Environmental Engineering And Engineering	7	5	12
	Telecommunications Engineering	5	9	14
	Medicine	6	4	10
	Nutrition And Dietetics	52	5	57
	Health Promotions	37	14	51
	Ancestral Knowledge	24	3	27
	Information Systems.	13	7	20
Area Of Residence	Rural	54	11	65
	Urban	103	42	145

Data collection and analysis

The data for this study was collected through validated surveys focused on students' opinions and experiences regarding the use of ChatGPT in completing academic activities. The interview protocol can be found in Appendix A. The instrument was previously validated in a related study that measures the use of the ChatGPT tool. The survey focused on six key constructs: compatibility (3 items), efficiency (4 items), perceived ease of use (3 items), perceived usefulness (3 items), satisfaction (3 items), and continued use intention (3 items). The survey included a section on informed consent, allowing participants to choose whether or not to complete the questionnaire.

Table 2. Structure of the questionnaire applied

Dimension	Code	Item
Sociodemographic	SC_01	Gender
	SC_02	Age
	SC_03	Ethnic group
	SC_04	Area of residence
	SC_05	The mother's educational level
	SC_06	Father's educational level
	SC_07	University that is studying
	SC_08	Career
	SC_09	Your university is
	SC_10	Semester
Compatibility	P1	Using ChatGPT is compatible with all aspects of my learning
	P2	I think that using ChatGPT fits well with the way I like to learn.
	P3	Using ChatGPT fits my learning style
Efficiency	P4	I use ChatGPT because it saves me time when performing my tasks.
	P5	I use ChatGPT because it makes my tasks easier.
	P6	I use ChatGPT because it improves the quality of my results
	P7	I use ChatGPT because it is useful for multitasking.
Perceived Ease of Use	P8	I find it easy to use ChatGPT.
	P9	My interaction with ChatGPT is clear and understandable.
	P10	I find it easy to make ChatGPT do what I want it to do."
Perceived Utility	P11	Using ChatGPT will improve my learning.
	P12	Using ChatGPT will increase my effectiveness.
	P13	I consider ChatGPT to be a useful tool for my learning.
Satisfaction	P14	I am satisfied enough with ChatGPT.
	P15	ChatGPT satisfies my educational needs.
	P16	I am satisfied with the performance of ChatGPT.
Intention of Continued Use	P17	I plan to continue using ChatGPT.
	P18	I want to continue using ChatGPT
	P19	I intend to recommend ChatGPT to my friends.

The study follows a cross-sectional, non-probabilistic design. The sampling technique employed was snowball sampling, as the survey was distributed through university professors who facilitated its dissemination to students via email and social media platforms.[12] The data analysis was conducted using the Google Colab platform, which allows the execution of R scripts. Principal Component Analysis (PCA) was employed as the primary statistical technique,[13] Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were performed to validate the construct structure and optimize the model.[14] PCA and EFA help identify groupings of observable variables corresponding to each latent construct, allowing for dimensionality reduction and the elimination of redundant or unrepresentative items. This ensures that each construct is composed solely of items that accurately reflect its meaning. These techniques enhance the precision and fit of the Structural Equation Modeling (SEM).[15,16,17]

Structural Equation Modeling (SEM) enabled the construction and adjustment of a new model based on the responses obtained.[18] Fit indices such as the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA) were utilized to validate the proposed model. This approach allowed for the evaluation of direct and indirect relationships among variables, providing a comprehensive understanding of the factors influencing satisfaction and the intention to use ChatGPT.[19,20]

RESULTS

Exploratory and confirmatory factor analysis

In the Exploratory Factor Analysis (EFA), four underlying factors were identified using the Maximum Likelihood (ML) method and Varimax rotation to enhance interpretability. The factor loading matrix indicates that items P5, P4, and P6 load predominantly on Factor 1 (ML3), signifying a significant grouping of these items around a common construct. The factors explained 63 % of the total variance, with Factor 1 accounting for 19 %, followed by Factor 2 at 17 %. The fit indices were acceptable: RMSR = 0,04 and RMSEA = 0,094, with a TLI of 0,884, suggesting an adequate model for the exploratory data.

For the Confirmatory Factor Analysis (CFA), the global fit indices of the model proposed in the EFA were evaluated using the Likelihood Ratio Chi-Square test (289,5, p < 0,000). Although the RMSEA value indicated minor deficiencies, indices such as the TLI and BIC (-250,56) suggest a reasonable model fit. The average item communalities were 0,62, with uniqueness ranging from 0,05 to 0,65, supporting the convergent validity of the identified factors.

The EFA identified four significant factors that explain the underlying structure of the items, while the CFA confirmed an acceptable fit for the proposed model. These results highlight the methodological robustness and the relevance of the identified factors for analyzing the construct. Additional testing is recommended to validate the model in different samples and to assess its stability.

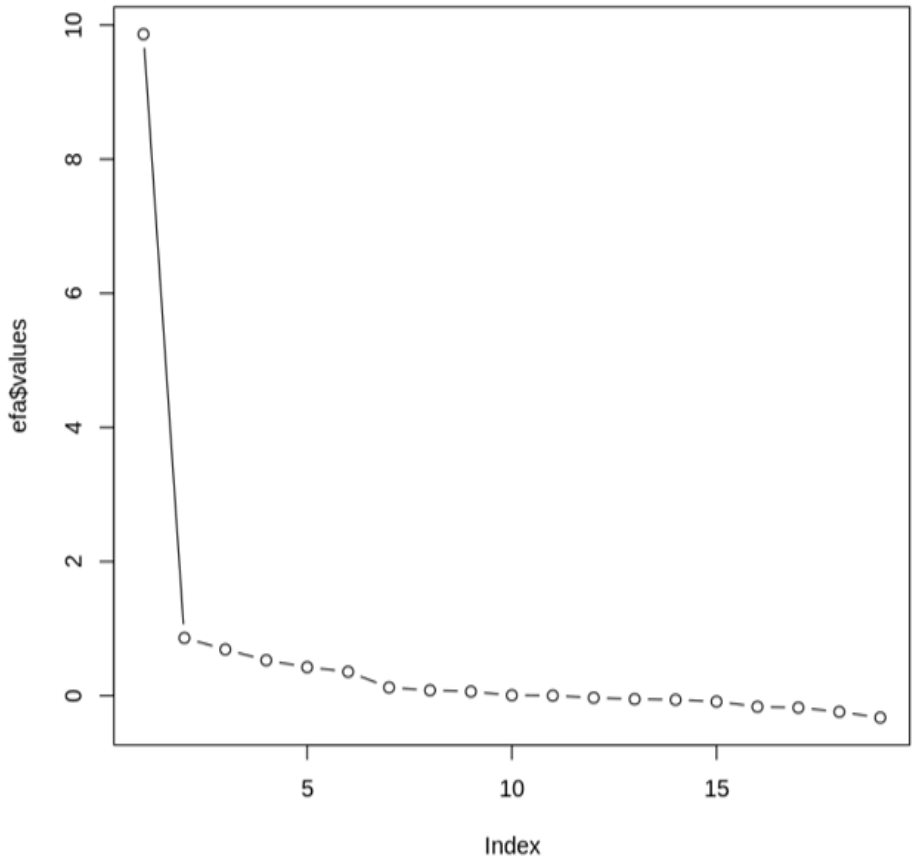

Figure 1. Scree Plot of the factor analysis

Description of Factors and Associated Items

Factor 1: Perceived Usefulness and Ease of Use (ML3). - This factor encompasses items related to the perception of ChatGPT's utility and ease of use. It includes items such as P5 ("I use ChatGPT because it simplifies my tasks"), P6 ("I use ChatGPT because it improves the quality of my results"), and P9 ("My interaction with

ChatGPT is clear and understandable"). These elements suggest that Factor 1 represents how users value the tool in terms of its efficiency and accessibility.

Factor 2: Satisfaction with Experience and Performance (ML2). - Factor 2 comprises items reflecting user satisfaction with ChatGPT's performance. Key items include P14 ("I am sufficiently satisfied with ChatGPT"), P15 ("ChatGPT meets my educational needs"), and P16 ("I am satisfied with ChatGPT's performance"). This factor measures the overall positive experience associated with using ChatGPT.

Factor 3: Alignment with Learning Style and Effectiveness (ML4). - This factor groups items highlighting how ChatGPT complements learning styles and enhances educational effectiveness. Examples include P1 ("Using ChatGPT is compatible with all aspects of my learning"), P2 ("I believe ChatGPT aligns well with my preferred way of learning"), and P3 ("Using ChatGPT fits my learning style"). - This factor emphasizes the tool's alignment with individual learning preferences.

Factor 4: Future Use Intention and Recommendation (ML1). - This factor includes items related to continued use and recommendation of ChatGPT, such as P17 ("I plan to keep using ChatGPT"), P18 ("I want to keep using ChatGPT"), and P19 ("I intend to recommend ChatGPT to my friends"). It represents users' willingness to continue engaging with the tool and to share it with others.

Each factor provides a distinct perspective on users' perceptions and attitudes, illustrating how different aspects of ChatGPT influence its adoption and use in academic activities.

Structural equations

Structural Equation Modeling (SEM) was conducted to evaluate a theoretical model based on the dimensions previously identified through Exploratory Factor Analysis (EFA). The model includes four latent factors: Perceived Usefulness and Ease of Use (ML3), Satisfaction with Experience (ML2), Compatibility with Learning (ML4), and Future Use Intention (ML1). This approach enabled the examination of underlying relationships among the factors and items, as well as the overall fit of the model.

Model Fitting

The model fit indices are summarized in the "SEM Fit Indices Table." Although the chi-square statistic (χ^2 = 403,545, $p < 0,001$) indicates an imperfect fit, it is important to consider that this statistic is highly sensitive to sample size (n = 210). Other indices provide a more nuanced view of the model fit:

- The Comparative Fit Index (CFI) is 0,876, indicating a reasonable fit compared to the null model.
- The Tucker-Lewis Index (TLI) is 0,851, slightly below the recommended threshold of 0,90.
- The Root Mean Square Error of Approximation (RMSEA) is 0,111, with a 90 % confidence interval between 0,099 and 0,122, suggesting a marginal fit.
- The Standardized Root Mean Square Residual (SRMR) is 0,064, within the acceptable range (< 0,08), indicating low residual discrepancies.

Model Parameters

The latent factors demonstrate significant associations with the items, as evidenced by the standardized factor loadings. For example, in the ML3 factor (Perceived Usefulness and Ease of Use), items P5 ("I use ChatGPT because it simplifies my tasks") and P4 ("I use ChatGPT because it saves me time") have high loadings of 0,85 and 0,81, respectively. Similarly, in ML2 (Satisfaction with Experience), item P16 ("I am satisfied with ChatGPT's performance") shows a significant loading of 0,82. In ML1 (Future Use Intention), item P18 ("I want to continue using ChatGPT") stands out with a factor loading of 0,78. All items exhibit statistical significance ($p < 0,001$), confirming their validity in representing the factors.

The results revealed a correlation greater than 0,9 between ML3 (Perceived Usefulness and Ease of Use) and ML4 (Compatibility with Learning), which may indicate conceptual redundancy between these constructs.

Figure 2 presents the proposed Structural Equation Modeling (SEM) framework, which includes four latent factors: ML1 (Future Use Intention and Recommendation), ML4 (Compatibility with Learning), ML2 (Satisfaction with Experience), and ML3 (Perceived Usefulness and Ease of Use). Each factor is associated with a set of observed indicators (items) and their respective standardized factor loadings.

Factor Loadings: The item loadings on the factors are all significant, ranging from 0,58 (P8 in ML3) to 0,90 (P15 in ML2). This suggests that the items are strongly associated with their respective factors, indicating good convergent validity.

High Correlations: A high correlation was observed between ML4 and ML1 (1,00) and between ML4 and ML2 (0,92), which may indicate conceptual redundancy among these factors. This suggests the potential need to merge factors or revise the theoretical structure.

Most Representative Items: High-loading items, such as P5 (0,85 in ML3) and P15 (0,90 in ML2), are the most representative of their respective factors. This indicates that these items significantly contribute to the measurement of the latent constructs.

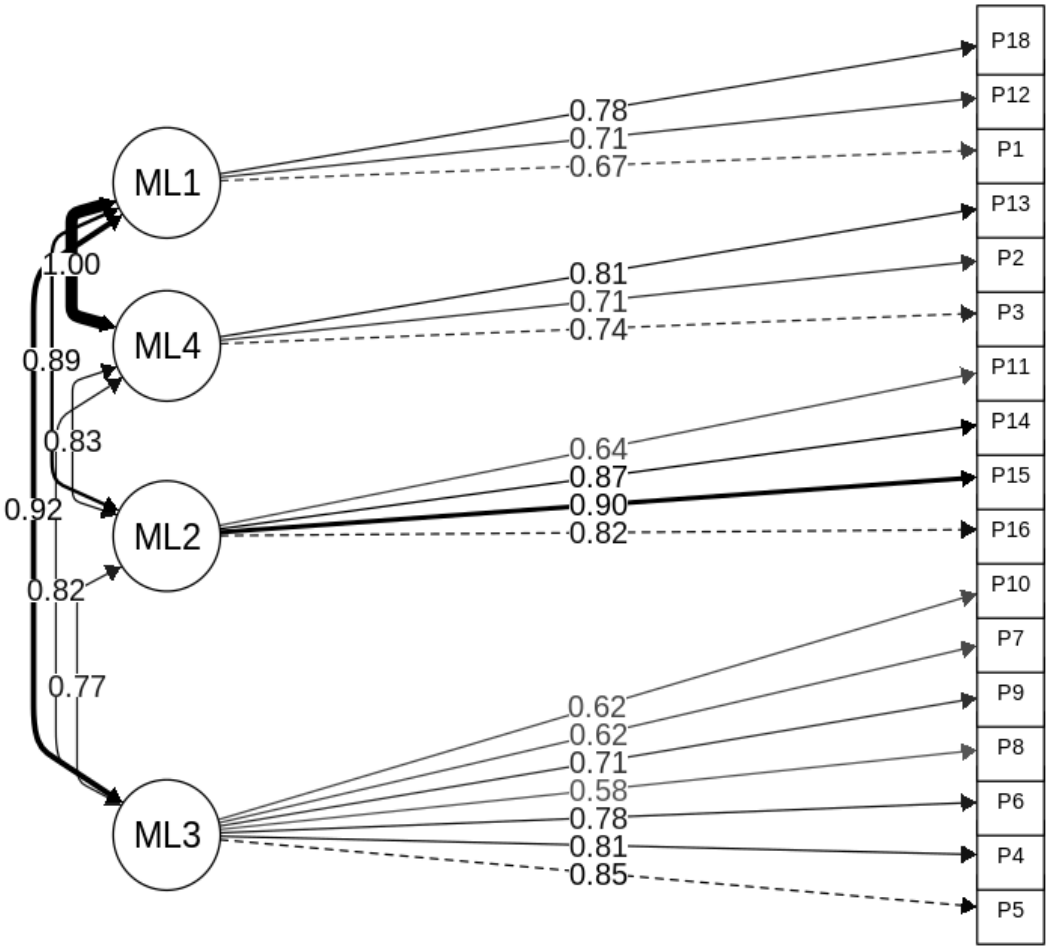

Figure 2. Diagram of the System of Structural Equations

DISCUSSION

This study validated a theoretical model based on Structural Equation Modeling (SEM) designed to measure perceptions and behaviors related to the use of ChatGPT in educational contexts. The findings provide significant insights that not only confirm the convergent and discriminant validity of the instrument but also highlight critical aspects regarding the factorial structure and overall model fit.

The latent factors ML1 (Future Use Intention and Recommendation), ML2 (Satisfaction with Experience), ML3 (Perceived Usefulness and Ease of Use), and ML4 (Compatibility with Learning) exhibited significant factor loadings ($p < 0,001$), with values ranging from 0,576 to 0,902. This range indicates that the selected items effectively capture the latent constructs, providing robust evidence of convergent validity.

The global fit indices present mixed results. On the one hand, the SRMR (0,064) indicates low residual discrepancies between the observed and estimated covariance matrices, suggesting that the model reasonably reproduces the data. On the other hand, the RMSEA (0,111) and its confidence intervals (0,099–0,122) exceed the recommended threshold of 0,08, reflecting a marginal fit. This finding aligns with research indicating that complex models with multiple factors often face challenges in achieving optimal fit.

The CFI (0,876) and TLI (0,851), although below the standard of 0,90, are close to acceptable values. These results highlight the need to make adjustments to the model to improve its parsimony and global fit, such as the elimination of redundant items or the combination of highly correlated factors.

Particularly, items such as P5 ("I use ChatGPT because it simplifies my tasks") and P16 ("I am satisfied with ChatGPT's performance") stand out with factor loadings exceeding 0,80. This supports previous research, such as that of,[21,22,23] that identified perceived usefulness and satisfaction as key predictors of technology acceptance in educational settings. Furthermore, the high factor loadings for items related to future use intention highlight the positive impact of ChatGPT on students' willingness to continue using this tool, aligning with the findings of studies such as those by[24] in the context of AI-assisted learning.

A notable aspect of the model is the high correlation observed between ML3 (Perceived Usefulness and Ease of Use) and ML4 (Compatibility with Learning) (r=0,92). While this relationship could be interpreted as

conceptual redundancy, it may also reflect students' integrated perception of how ChatGPT's ease of use directly supports its alignment with their learning styles. Recent studies, such as those by,[25] have documented similar phenomena, emphasizing how the perception of technological compatibility is closely linked to perceived usefulness, particularly in autonomous learning contexts.

The results have significant implications at both theoretical and practical levels. From a theoretical perspective, this study validates the proposed four-factor structure, providing a solid conceptual framework for evaluating the impact of tools like ChatGPT in educational settings. However, the high correlation between certain factors suggests the need to reconsider the factorial structure to enhance its parsimony and conceptual clarity.

From a practical perspective, the model provides evidence that ChatGPT is perceived as a useful, easy-to-use tool aligned with students' learning styles. This finding is particularly relevant for educational institutions aiming to integrate artificial intelligence technologies into their programs, as it underscores the importance of satisfaction and perceived usefulness in driving technology adoption.[26]

In conclusion, this study validates a robust theoretical model for measuring perceptions and behaviors related to the use of ChatGPT in education. While the findings highlight areas for improvement, such as simplifying the factorial structure, they also emphasize the positive impact of this tool on students' learning experiences. These results not only contribute to the field of educational research but also provide practical guidance for implementing AI technologies in academic settings.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Edgar Rolando Morales Caluña, Dario Javier Cervantes Diaz, Cristian Ismael Morales Caluña, Fernando Xavier Altamirano Capelo.

Writing – Original draft: Edgar Rolando Morales Caluña, Dario Javier Cervantes Diaz, Cristian Ismael Morales Caluña, Fernando Xavier Altamirano Capelo.

Writing – proofreading and editing: Edgar Rolando Morales Caluña, Dario Javier Cervantes Diaz, Cristian Ismael Morales Caluña, Fernando Xavier Altamirano Capelo.