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Research Article

Measuring student receptivity to ChatGPT in higher education: A case study from Peru

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ABSTRACT

The continuous rise of artificial intelligence tools in educational settings highlights the importance of understanding how students position themselves in relation to these technologies. This study aims to analyze the attitudes toward ChatGPT among Peruvian university students, considering the cognitive, affective, and behavioral components, as well as the metric properties of the instrument. A quantitative approach was employed, with a descriptive-comparative and instrumental research design, involving 464 Peruvian students from different academic disciplines. The results indicated that, after performing confirmatory factor analysis, the final model consisted of 33 items assessing attitudes toward ChatGPT across cognitive, affective, and behavioral components, with slightly acceptable fit indices (χ^2/df, $p < 0.05$, SRMR, RMSEA, TLI, CFI, and GFI) and adequate factor loadings ($\lambda > 0.3$). In addition, the instrument showed satisfactory reliability evidence ($\alpha_{ordinal}$ and $\Omega_{ordinal} > 0.7$). Another finding revealed that engineering students exhibited a significantly more favorable affective attitude toward ChatGPT ($p = 0.03$) compared to students from the social and natural sciences. No significant differences ($p > 0.05$) were found in students' attitudes based on sex or age. In conclusion, although future engineers display a more favorable affective attitude than students from other disciplines, overall attitudes toward ChatGPT do not show relevant differences across other sociodemographic factors. Moreover, the instrument proved to be valid and reliable with 33 items, thus representing a solid and less dense tool for future research.

Keywords: ChatGPT, attitudes, behavioral, cognitive, affective

INTRODUCTION

Currently, artificial intelligence (AI) has transformed multiple aspects of daily life, revolutionizing how people interact with technology and process information (Smith & Smith, 2024). Its presence extends across various domains, from virtual assistants and recommendation algorithms to automation systems and data analytics, optimizing tasks in sectors such as communication, healthcare, industry, and entertainment (Al Naqbi et al., 2024). Thanks to its capacity to process large volumes of data and generate contextually adapted responses, AI has enhanced decision-making efficiency, facilitated problem-solving, and simplified numerous complex processes, thereby redefining how people access knowledge and manage their daily activities (Humr et al., 2025).

Among AI-based tools, language models such as ChatGPT have gained significant popularity within the university context, where they are used for a variety of academic tasks (García Castro et al., 2024; von Garrel & Mayer, 2023). Its accessibility and ease of use have enabled the rapid integration of this technology into learning environments, providing new forms of support for academic development (Ali et al., 2024), especially in the area of information literacy (Chura-Quispe et al., 2025). However, its growing adoption has also sparked debates regarding its implications for the teaching-learning process, particularly with respect to the development of critical thinking, student autonomy, and academic ethics (Estrada et al., 2024).

To understand its role in education, it is essential to define what ChatGPT is. It is an AI model based on natural language processing, developed by OpenAI (Roumeliotis & Tselikas, 2023). Its design is grounded in advanced neural networks, specifically transformer architectures, which enable it to analyze large datasets and generate coherent and contextually appropriate responses in real time (Ray, 2023). Due to its training on massive textual datasets, it can provide detailed and contextualized information on a wide range of topics (Dwivedi et al., 2023). However, it is important to note that its knowledge is limited to the data on which it was trained and that it cannot access real-time information or learn from new interactions beyond its pre-defined updates (Kleib et al., 2024).

Its main features include the ability to produce fluent and structured responses, versatility across different academic fields, and accessibility through multiple platforms (Hassani & Silva, 2023). Its design allows it to adapt to different types of queries, from detailed explanations to concise answers, depending on user needs (Liu, 2024). Furthermore, its machine learning capabilities allow it to simulate human-like interactions with a high degree of coherence and precision, adjusting the tone and complexity of its responses based on context (Menon & Shilpa, 2023). Additionally, its ability to process vast amounts of information in seconds makes it an effective tool for exploring various topics (Hasanein & Sobaih, 2023). Nonetheless, since it does not understand the meaning of texts as a human would, its responses may contain inaccuracies or biases inherent in the data on which it was trained. This requires users to maintain a critical perspective when interpreting its outputs (Laizure, 2024).

Practically speaking, ChatGPT offers several advantages that make it a valuable tool for university students. First, it facilitates immediate access to relevant information, enabling quick and efficient resolution of questions (Raj et al., 2023). It also enhances academic productivity by streamlining the writing of documents, generating summaries of lengthy texts, and providing references for academic work (Khalifa & Albadawy, 2024). Moreover, it fosters creativity by offering suggestions and ideas for projects and essays, allowing students to explore new perspectives and approaches in their research (Rahman & Watanobe, 2023). Another significant advantage is its 24/7 availability, making it an accessible resource for those who require support outside conventional academic hours—whether to review concepts before an exam, structure a presentation, or reinforce knowledge in various subjects (Crompton & Burke, 2024). Additionally, its adaptability to different learning styles enables students to personalize its use according to their specific needs, contributing to a more flexible and autonomous educational experience (Oates & Johnson, 2025).

Despite its benefits, ChatGPT also presents disadvantages that must be carefully considered. One major limitation is the possibility of receiving inaccurate, outdated, or biased information, which can negatively affect the quality of academic work if students do not critically verify their sources (Mondal & Mondal, 2023). Moreover, excessive reliance on the tool can lead to dependency and hinder the development of critical thinking, as some students may accept generated responses without reflection, questioning, or analysis. This may undermine essential skills such as argumentation and problem-solving (Suriano et al., 2025). Another concern is the risk of plagiarism, as some users might copy responses directly without modification or proper attribution, thereby compromising academic integrity and discouraging originality in knowledge production (Elkhatat, 2023).

Given its growing presence in academia, ChatGPT has sparked debates about its impact on education. Its integration into the university setting presents opportunities to enhance teaching and learning, particularly when it is used as a complementary tool rather than a substitute for the student's intellectual effort (Deng et al., 2025). However, its appropriate use requires pedagogical strategies that promote critical thinking, information verification, and the development of digital competencies (Isiaku et al., 2024). In this regard, educators play a crucial role in regulating and guiding the use of this technology, ensuring that students apply it ethically and responsibly throughout their academic formation (Kovari et al., 2025).

In this context, the ethical dimension of ChatGPT's use in higher education becomes increasingly relevant. It is not enough to teach students how to leverage its functionalities; it is also essential to instill principles of academic integrity and originality in intellectual work (Memarian & Doleck, 2023). Universities must establish clear guidelines regulating its use, fostering transparency in academic output and preventing practices such as plagiarism or excessive reliance on AI tools (Estrada et al., 2025). The implementation of codes of conduct and teacher guidance on responsible ChatGPT use can be decisive in the ethical integration of AI into the university environment (Farhi et al., 2023).

Based on the above, university students' attitudes toward ChatGPT use represent a key factor in understanding the integration of this technology into academic life (Acosta et al., 2024). This construct refers to their predisposition to accept, use, and value this AI tool in their learning. Attitude is composed of three main dimensions: cognitive, which encompasses beliefs and perceptions regarding ChatGPT's usefulness, accuracy, or reliability (Svenningsson, 2020); affective, which relates to emotions and feelings toward its use, such as enthusiasm, curiosity, or apprehension (Suh & Ahn, 2022); and behavioral, which involves observable actions toward the technology, such as adoption or rejection, manifested through the frequency and context of its use in academic activities (Ankiewicz, 2019).

While some view it as an innovative tool that saves time, improves the quality of work, and provides immediate assistance, others express concerns about the potential to foster technological dependence and diminish students' capacity for analysis and reflection (Naznin et al., 2025). Therefore, it is necessary to explore how university students perceive this technology and what their primary uses are. A detailed analysis of these attitudes will allow for a better understanding of the benefits and risks associated with its implementation in higher education.

Although identifying students' attitudes toward AI tools such as ChatGPT is essential, it is equally important to use instruments adapted to the local context for accurate assessment. Recent studies have focused on understanding the structure of attitudes toward AI, emphasizing bidimensional models centered on positive and negative attitudes (Schepman & Rodway, 2022; Seo & Ahn, 2022; Tien, 2024). This approach has been validated in contexts such as nursing professionals (Yilmaz et al., 2025), university students (Marengo et al., 2025), and military applications (Hadlington et al., 2023), demonstrating robust structure and adequate psychometric validity.

Although a tradition exists of evaluating attitudes based on positive or negative dimensions, current research increasingly points to the need for a more academically grounded and socially informed framework. This highlights the relevance of revisiting the classical tridimensional structure, comprising the cognitive, affective, and behavioral components (Eagly & Chaiken, 1993). This approach integrates beliefs or knowledge (cognitive component), emotions or affective responses (affective component), and behavioral or intentional dispositions toward action (behavioral component), enabling a deeper understanding of attitudes toward ChatGPT (Stein et al., 2024).

Nevertheless, limited attention to this triadic structure in the Peruvian context has created a knowledge gap regarding its applicability. Applying instruments without proper adaptation may result in interpretative distortions. In Peru, attitudes toward emerging technologies like ChatGPT are shaped by a landscape marked by digital divides, educational heterogeneity, regional diversity, and unequal levels of literacy—factors that require context-sensitive tools.

Other studies have assessed students' attitudes toward ChatGPT in university settings. In Peru, Acosta et al. (2024) found that these attitudes were primarily influenced by the affective component and, to a lesser extent, the cognitive one, with no moderating effects from gender or age. Similarly, Estrada et al. (2024) concluded that students' attitudes toward ChatGPT as a learning tool were moderate across affective, cognitive, and behavioral dimensions. While students appreciated its utility and enjoyed its use, they also expressed concerns about the possibility of inaccurate results. In Hungary, Fajt and Schiller (2025) found that students perceived ChatGPT as moderately useful and easy to use but had concerns about its reliability and potential misuse. Their willingness to use it was closely linked to this perception, and while students with AI experience considered it beneficial for academic tasks, its integration into educational environments required careful consideration of ethical implications—especially regarding plagiarism.

This research is justified as it seeks to identify usage patterns, perceptions, and challenges students face when incorporating ChatGPT into their academic lives. It also aims to provide metric evidence of the attitudinal structure toward ChatGPT with internal coherence and conceptual relevance, based on cognitive, affective, and behavioral components in the Peruvian context. This will allow for a more efficient understanding of how university students perceive, feel about, and are inclined to use this AI tool. Having an adapted and validated instrument facilitates an initial diagnosis of educational needs in higher education. Additionally, the findings may inform the development of strategies and regulations that promote responsible and informed use of AI in academia. Based on these results, it will be possible to establish recommendations that maximize the benefits of ChatGPT without compromising the development of essential skills such as reflection, analysis, and creativity.

Finally, the objective of this research was to explore the attitudes of Peruvian university students toward ChatGPT and to analyze the metric properties of the instrument within the Peruvian context.

METHOD

This study employed a descriptive-comparative and instrumental research design. Its primary aim was to explore university students' attitudes toward ChatGPT and to examine potential differences based on gender, age, and academic faculty. Additionally, it is considered instrumental as it seeks to evaluate the metric properties of an instrument adapted to the northeaster Peruvian Amazon context (Ato et al., 2013).

Participants

The target population consisted of all students enrolled at a public university located in the northeaster Peruvian Amazon. The sample included 464 students, selected through probabilistic sampling with a 95% confidence level and a 5% significance level. Of the total participants, 62.1% were male and 37.9% female. Regarding age distribution, 48.1% were 19 years old or younger, 38.6% were between 20 and 23 years old, 9.7% were between 24 and 27 years old, and 3.7% were older than 27. In terms of academic faculties, 46.3% belonged to social and business sciences, 27.8% to natural and applied sciences, and 25.9% to engineering (**Table 1**).

Instrument

Data were collected using a structured digital questionnaire developed through the Google Forms platform. In the first section, students were asked to provide sociodemographic and academic information, including variables such as sex, age, and academic faculty.

In the second section, the attitudes toward ChatGPT questionnaire, developed by Acosta et al. (2024), was administered. This instrument assesses perceptions and knowledge about this tool, emotions and predisposition toward its use, as well as behaviors associated with its implementation in the academic context. It consists of 40 items rated on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). These items are grouped into three dimensions: cognitive component (14 items), affective component (12 items), and behavioral component (14 items). Following the confirmatory factor analysis (CFA), the instrument was refined to 33 items distributed across the three original dimensions, showing adequate validity and reliability indices.

Table 1. Sample distribution

Variables	Category	n = 464	Percentage (%)
Sex	Male	288	62.10
	Female	176	37.90
Age	19 years or younger	223	48.10
	20 to 23 years	179	38.60
	24 to 27 years	45	9.70
	Over 27 years	17	3.70
Faculty	Social and business sciences	215	46.30
	Natural and applied sciences	129	27.80
	Engineering	120	25.90

Procedures

Prior to data collection, authorization was obtained from the relevant university authorities. Students were then invited to participate via WhatsApp messages, which included a link to the survey along with an explanation of the research purpose. Before completing the instruments, participants were asked to provide informed consent and were given clear instructions to ensure accurate responses. The data collection process took approximately 10 minutes per respondent. Once the target sample size of 464 participants was reached, access to the survey was disabled to preserve the integrity of the collected data.

Data Analysis

Data analysis was conducted using R Studio software, version 2024.04.1. Specifically, the "corrplot," "ggplot2," and "polycor" packages were used to examine the polychoric correlations among the 40 items of the instrument. Additionally, the "lavaan," "semPlot," and "semTools" packages were employed to perform CFA and to estimate the reliability of the dimensions (cognitive, affective, and behavioral components).

Initially, the behavior of the items was analyzed based on participants' responses. Descriptive statistics were calculated, including the mean, standard deviation, corrected item-total correlation, and communalities, as well as values such as skewness, kurtosis, and the impact on reliability if an item were deleted. Subsequently, the internal structure of the instrument was assessed through CFA, as the goal was to confirm a pre-established theoretical structure (Cattell, 1966) rather than to develop a new model. Given the ordinal nature of the items, the weighted least squares mean and variance adjusted method (WLSMV) was applied. The fit indices examined included Chi-square, comparative fit index (CFI ≥ 0.95), Tucker-Lewis index (TLI ≥ 0.95), goodness-of-fit index (GFI ≥ 0.95), root mean square error of approximation (RMSEA ≤ 0.08), and standardized root mean square residual (SRMR < 0.06) (Hu & Bentler, 1999).

In addition, correlations among latent variables were estimated, and internal consistency was evaluated using Cronbach's alpha and McDonald's omega, with reliability coefficients greater than 0.7 expected for each factor (Ventura-León, 2017).

Finally, comparisons of the components of attitudes toward ChatGPT were conducted based on sociodemographic variables, including sex (female and male), age groups (≤ 19 years, 20–23, 24–27, and ≥ 28 years), and academic faculty (engineering, social and business sciences, and natural and applied sciences). For this purpose, non-parametric tests were used: the Mann-Whitney U test for comparisons between two independent groups, and the Kruskal-Wallis H test for comparisons across three groups, with interpretation based on statistical significance ($p < 0.05$).

Ethical Considerations

This study was conducted in accordance with the principles outlined in the Declaration of Helsinki. Students were provided with clear and detailed information about the objectives and characteristics of the research, and their informed consent was obtained voluntarily. Participants were assured of their right to freely participate and to withdraw at any time without consequences. Additionally, measures were taken to safeguard privacy and data confidentiality, ensuring participant anonymity and the secure handling of all collected information.

Table 2. Item analysis of the instrument

Items	M	SD	Skewness	Kurtosis	Communality	CITC	If deleted	
							Cronbach's alpha	McDonald's omega
P10	3.18	0.92	−0.97	0.09	0.63	0.62	0.80	0.81
P11	3.22	0.89	−0.97	0.14	0.62	0.63	0.80	0.81
P12	3.18	0.88	−0.90	0.05	0.62	0.63	0.80	0.81
P13	3.21	0.87	−0.93	0.11	0.62	0.64	0.80	0.81
P14	3.18	1.05	−1.06	−0.17	0.32	0.45	0.81	0.83
P15	2.91	0.93	−0.02	−0.32	0.00	0.09	0.83	0.85
P16	2.90	0.87	−0.04	−0.15	0.00	0.08	0.83	0.85
P17	3.17	0.87	−0.88	0.07	0.47	0.56	0.80	0.82
P28	3.07	0.87	−0.68	−0.23	0.44	0.56	0.80	0.82
P29	3.23	0.86	−1.05	0.51	0.52	0.60	0.80	0.82
P30	3.06	0.95	−0.83	−0.21	0.16	0.36	0.82	0.84
P31	2.95	1.06	−0.70	−0.73	0.20	0.42	0.81	0.83
P32	3.03	0.85	−0.68	−0.05	0.13	0.36	0.82	0.84
P33	2.97	1.07	−0.73	−0.72	0.17	0.38	0.82	0.84
P4	3.38	1.01	−0.47	−0.25	0.00	0.31	0.50	0.58
P5	3.44	0.94	−0.62	−0.01	0.00	0.38	0.49	0.57
P6	3.44	0.92	−0.67	0.21	0.00	0.35	0.49	0.58
P7	2.78	0.90	0.12	−0.27	0.00	−0.08	0.59	0.65
P8	3.31	0.89	−1.23	0.73	0.51	0.36	0.49	0.55
P9	3.26	0.96	−1.17	0.29	0.44	0.31	0.50	0.56
P18	3.09	0.91	−0.83	−0.06	0.44	0.28	0.51	0.57
P19	3.22	0.89	−1.07	0.41	0.58	0.32	0.50	0.55
P20	3.12	0.93	−0.88	−0.09	0.58	0.23	0.52	0.57
P21	2.97	0.89	0.73	−0.13	0.17	0.01	0.57	0.63
P34	2.94	1.00	0.83	−0.37	0.21	0.11	0.55	0.62
P35	2.97	1.04	0.83	−0.50	0.19	0.11	0.56	0.62
P1	3.54	0.97	−0.63	0.26	0.01	0.18	0.81	0.83
P2	3.47	0.95	−0.67	0.23	0.02	0.18	0.81	0.83
P3	3.43	0.98	−0.58	0.01	0.01	0.21	0.81	0.83
P22	2.96	0.85	−0.49	−0.39	0.37	0.47	0.79	0.81
P23	3.09	0.86	−0.73	−0.07	0.43	0.53	0.79	0.81
P24	3.08	0.84	−0.70	−0.04	0.45	0.55	0.79	0.80
P25	3.13	1.03	−0.94	−0.32	0.51	0.57	0.78	0.80
P26	3.19	0.98	−1.07	0.10	0.41	0.52	0.79	0.81
P27	2.76	0.99	0.08	−0.51	0.01	0.20	0.81	0.83
P36	3.18	1.02	−1.11	0.04	0.45	0.49	0.79	0.81
P37	3.16	0.94	−1.04	0.23	0.50	0.52	0.79	0.81
P38	3.20	1.00	−1.13	0.17	0.53	0.55	0.78	0.80
P39	3.19	1.00	−1.11	0.12	0.56	0.55	0.78	0.80
P40	3.11	1.01	−0.98	−0.14	0.46	0.50	0.79	0.81

RESULTS

In **Table 2**, a descriptive analysis of the 40 items from the test measuring attitudes toward ChatGPT is presented. The item means range from 2.76 to 3.54, with standard deviations ranging between 0.84 and 1.07. Regarding item skewness, the majority show negative skewness, indicating a tail to the left, except for items 7, 21, 34, 35, and 27, which exhibit positive skewness. Item kurtosis falls within the ±1 interval. Specifically, items 10, 11, 12, 13, 17, 6, 8, 9, 19, 1, 2, and 3 show a slight tendency toward leptokurtosis (> 0), while the remaining items display platykurtic behavior (< 0). In terms of communalities, items 15, 16, 31, 32, 33, 4, 5, 6, 7, 21, 34, 35, 1, 2, 3, and 27 scored below 0.3, suggesting a weak association with the extracted factors. Regarding corrected item-total correlations (CITC), items 15, 16, 7, 20, 21, 34, 35, 1, 2, 3, and 27 showed minimal contribution to the measurement of the construct. Furthermore, items 15, 16, 32, and 33 would improve the instrument's overall reliability the most if removed.

With regard to the polychoric correlations presented in **Figure 1**, it was observed that the items with more than 13 correlations above 0.4 were items 10, 11, 12, 13, and 19. Item 7 and item 27 did not exhibit any correlations above 0.4 with the other items in the construct. Meanwhile, items 15, 16, and 21 each showed only one significant correlation. The remaining items displayed between 2 and 12 correlations exceeding 0.4.

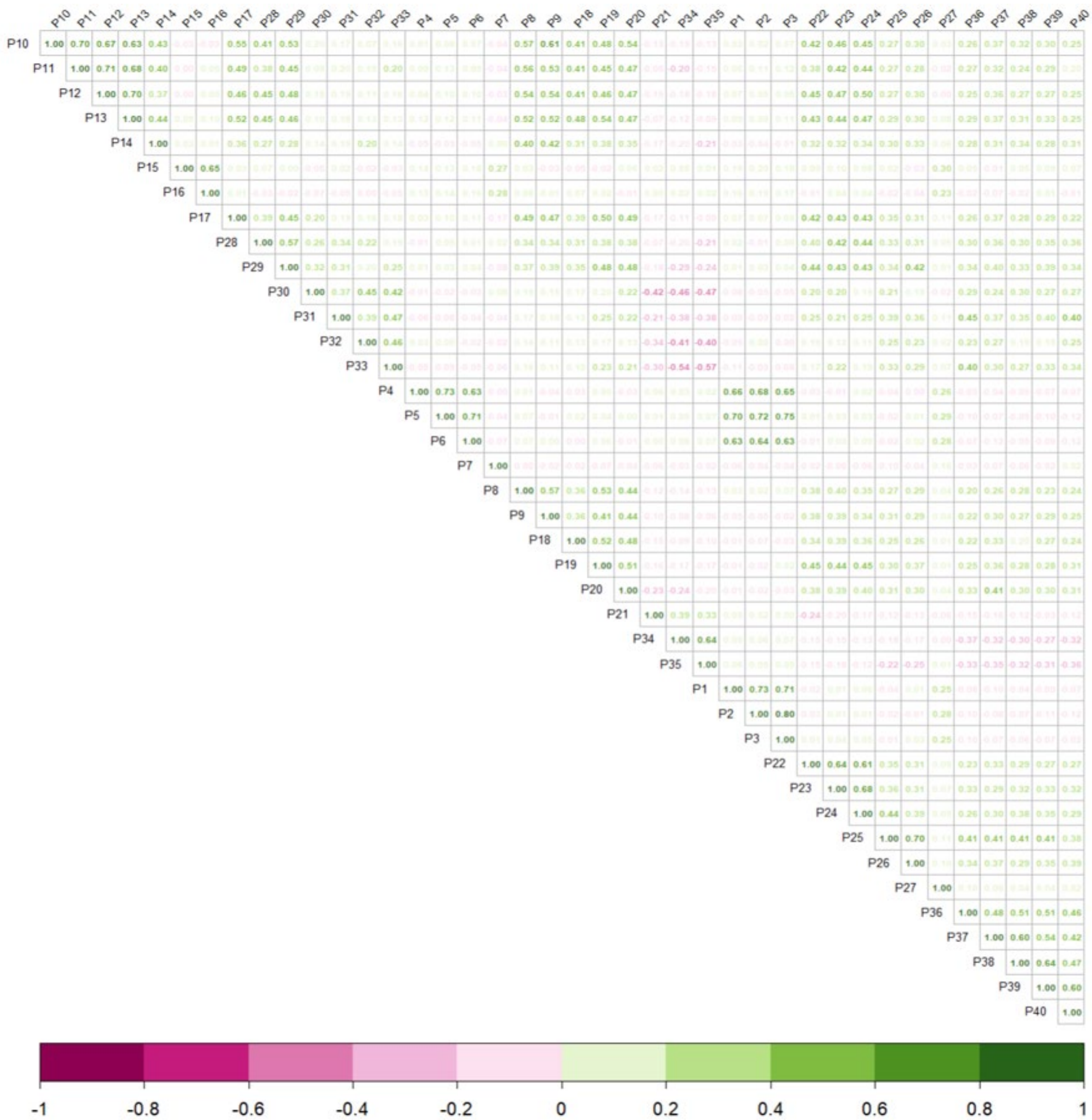

Figure 1. Polychoric correlations among the items of the construct (Source: Authors)

Table 3. Fit indices of the instrument models

Models	χ^2	df	p	SRMR	RMSEA (90%)	TLI	CFI	GFI
M1	31,155.80	737	0.00	0.202	0.189 (0.187–0.192)	0.680	0.697	0.744
M2	26,101.34	492	0.00	0.222	0.181(0.177–0.185)	0.702	0.722	0.760
M3	9,785.72	411	0.00	0.140	0.128(0.123–0.133)	0.813	0.854	0.873

Note: M1: Initial model; M2: Model with items 7, 21, 35, 34, 15, 16, and 27 removed; M3: Model with item covariance adjustments based on modification indices.

Table 3 presents the fit indices of the models of attitudes toward ChatGPT. M1 corresponds with the initial model with 40 items; M2 contains 33 items, as items 7, 21, 35, 34, 15, 16, and 27 were removed due to factor loadings lower than 0.3, low or near-zero correlations with other items (**Figure 1**), and low scores in IHC and H2 (**Table 1**). M3 also retains 33 items but is based on the covariance established from modification indices greater than 20, applied to items belonging to the same construct, following the structure of model 2.

When comparing the three models, all show p-values below the significance threshold ($p < 0.05$). Regarding the chi-square/degrees of freedom ratio (χ^2/df), M1 yielded 42.27, M2 = 53.05, and M3 = 23.80, indicating that M3 is more parsimonious. For the SRMR, although all models exceeded the recommended threshold of 0.08,

Table 4. Factor loadings of the attitudes toward ChatGPT model

Items	Cognitive component	Affective component	Behavioral component
Item 10	0.862		
Item 11	0.824		
Item 12	0.820		
Item 13	0.865		
Item 14	0.642		
Item 17	0.749		
Item 28	0.643		
Item 29	0.739		
Item 30	0.390		
Item 31	0.510		
Item 32	0.328		
Item 33	0.412		
Item 04		0.338	
Item 05		0.467	
Item 06		0.302	
Item 08		0.752	
Item 09		0.747	
Item 18		0.606	
Item 19		0.760	
Item 20		0.734	
Item 01			0.386
Item 02			0.424
Item 03			0.468
Item 22			0.663
Item 23			0.713
Item 24			0.734
Item 25			0.689
Item 26			0.669
Item 36			0.608
Item 37			0.661
Item 38			0.587
Item 39			0.606
Item 40			0.579

Table 5. Correlations and internal consistency of the attitudinal constructs toward ChatGPT

Variables	Cognitive component	Affective component	Behavioral component	$\alpha_{ordinal}$	$\omega_{ordinal}$
Cognitive component	1			0.89 (0.78–0.96)	0.90
Affective component	0.88	1		0.77 (0.41–0.95)	0.82
Behavioral component	0.81	0.9	1	0.86 (0.71–0.95)	0.90

M3 had the closest value at 0.140. As for RMSEA, all scores were above 0.07, but M3 again showed the most acceptable result at 0.128.

In none of the models presented in **Table 3** does the expected minimum threshold of 0.90 exceed, indicating that the theoretical structure still requires more thorough analysis. However, the most parsimonious model is M3, since its values (TLI = 0.813, CFI = 0.854, and GFI = 0.873) are sufficiently close to the expected threshold (0.90). Moreover, when applying the WLSMV model, lower values can occur with ordinal items (Li, 2015), which requires maintaining flexibility by considering values close to acceptable cut-off points (Xia & Yang, 2018). Therefore, combined with theoretical coherence and the stability observed in the factor loadings, it can be concluded that this model provides an adequate and practical fit for evaluating the construct of attitudes toward ChatGPT.

Table 4 presents the factor loadings for model 3 of attitudes toward ChatGPT. The findings indicate that, within the cognitive component, loadings range from 0.328 (item 32) to 0.865 (item 13). For the affective component, loadings vary between 0.338 (item 4) and 0.760 (item 19). In the behavioral component, the factor loadings range from 0.386 (item 1) to 0.734 (item 24).

Table 5 shows that the correlations between the components—cognitive-affective (0.88), cognitive-behavioral (0.90), and affective-behavioral (0.81)—are moderate and positive; all values exceed 0.7. Regarding

Table 6. Comparison of attitudes toward ChatGPT according to sociodemographic data

Variables	Cognitive component			Affective component			Behavioral component			GLOBAL		
	M	SD	p	M	SD	p	M	SD	p	M	SD	p
Sex												
M (n = 288)	37.44	7.13	0.97	26.35	4.26	0.62	41.57	7.04	0.50	105.36	16.38	0.91
F (n = 176)	37.47	6.59		26.11	4.45		41.96	6.65		105.54	15.26	
Age												
≤ 19 (n = 223)	37.58	6.38	0.55	25.87	4.21	0.051	41.42	6.45	0.11	104.87	14.75	0.13
20-23 (n = 179)	37.40	7.16		26.61	4.50		41.71	7.10		105.72	16.46	
24-27 (n = 45)	38.47	7.65		27.31	3.87		43.56	7.76		109.33	17.85	
28 ≤ (n = 17)	33.59	8.48		24.94	4.58		40.88	7.65		99.41	19.06	
Faculty												
SBS (n = 215)	37.35	6.75	0.23	26.32	4.26	0.03	41.85	6.66	0.23	105.51	15.36	0.091
NAS (n = 129)	36.99	7.25		25.40	4.83		40.95	7.23		103.35	17.05	
ENG (n = 120)	38.13	6.87		27.08	3.69		42.32	6.91		107.53	15.61	

Note: F = Female; M = Male; SBS = Social and business sciences; NAS = Natural and applied sciences; ENG = Engineering.

reliability indices, both ordinal alpha and omega for each construct demonstrate values above the 0.7 threshold. Specifically, the cognitive component showed α = 0.89 and ω = 0.90; the affective component had α = 0.77 and ω = 0.82; and the behavioral component reported α = 0.86 and ω = 0.90.

The findings presented in **Table 6** indicate that there are no significant differences between male and female students in their attitudes toward ChatGPT, nor in any of its components (COG = 0.97, AFF = 0.62, BEH = 0.50, GLOBAL = 0.91), as all p-values exceed the significance threshold. Similarly, no significant differences were found based on age (Cognitive component = 0.55, Affective component = 0.051, Behavioral component = 0.11, GLOBAL = 0.13). However, in relation to academic programs, no differences were found in the cognitive (p = 0.23), behavioral (p = 0.23), or global scores (p = 0.091). Nevertheless, a significant difference was observed in the affective component (p = 0.03). Students from engineering programs exhibited a more favorable affective attitude (mean [M] = 27.08, standard deviation [SD] = 3.69), followed by those from social and business sciences (M = 26.32, SD = 4.26), while students from natural sciences showed the least favorable affective attitude (M = 25.40, SD = 4.83).

DISCUSSION AND CONCLUSION

This study aimed to describe university students' attitudes toward ChatGPT and to examine the metric properties of the attitudes toward ChatGPT scale among this population. The findings confirmed that the instrument demonstrates favorable fit indices when items 7, 21, 35, 34, 15, 16, and 27 were removed due to low correlations and weak factor loadings. The version adapted to the Peruvian university context features a structure organized into three components: cognitive (12 items), affective (8 items), and behavioral (13 items). Additionally, no significant differences in attitudes were found based on gender or age. However, regarding academic discipline, engineering students showed a more favorable affective attitude than students in social and natural sciences.

The three-factor structure of the instrument is based on the theoretical model proposed by Mitcham (1994), which conceptualizes attitude as comprising cognitive, affective, and behavioral components. This framework was maintained throughout the study, aligning with classical social psychology despite the existence of bifactorial or unifactorial models in recent literature. Few studies support this triadic structure, one of which is by Stein et al. (2024), who, through the ATTARI-12 instrument, reaffirmed the classical attitude triad—cognition, emotion, and behavior. Nevertheless, much of the existing literature frames attitudes in terms of positivity/negativity in academic, health, or military contexts (Hadlington et al., 2023; Marengo et al., 2025; Schepman & Rodway, 2022; Seo & Ahn, 2022; Tien, 2024; Yilmaz et al., 2025), or around acceptance/fear (Sindermann et al., 2020), emotional intelligence, and decision-making (Almomani & Alnasraween, 2024). Some studies even adopt unidimensional structures (Köse et al., 2025). While the variety of factorial configurations may seem compelling, the complex nature of the construct requires a robust and versatile theoretical foundation to ensure its contextual suitability—in this case, for the Peruvian setting.

Specifically, the results showed that no significant gender differences were observed in any of the three attitude components (cognitive, affective, and behavioral), which aligns with recent studies suggesting that attitudes toward ChatGPT are shaped more by prior technological experience than gender (Acosta et al., 2024; Karafil & Uyar, 2025; Romero-Rodríguez et al., 2023; Yu et al., 2024). Although some research indicates similar knowledge and general attitudes across genders, men often report greater interest and self-perceived competence in technology-related skills (Beig & Qasim, 2023; Kovačević & Demić, 2024). These discrepancies are likely explained by cultural, age-related, and contextual factors. In the present sample, digital literacy levels were relatively homogeneous, likely due to the widespread and transversal use of ChatGPT, which shapes similar learning experiences across students.

Regarding age, no significant differences were found among the groups (≤ 19, 20–23, 24–27, ≥ 28), although students aged 24–27 showed slightly higher scores. Overall, the results reflect a notable uniformity in how students perceive and value ChatGPT. This aligns with previous research suggesting that age does not play a statistically significant role in predicting attitudinal behavior (Acosta et al., 2024; Bodani et al., 2023; Karafil & Uyar, 2025). In fact, variables such as technological training or country of residence appear to be more relevant. Even in contexts where senior students demonstrated greater conceptual understanding than juniors, no significant attitudinal differences were found between those groups (Kovačević & Demić, 2024). This suggests that university students are undergoing a generational normalization process, wherein traditional age differences are increasingly replaced by situational factors in educational settings.

In terms of academic discipline, significant differences were found only in the affective component, with engineering students reporting more favorable emotional attitudes toward ChatGPT than their peers in social and natural sciences. While cognitive and behavioral perceptions were similar across fields, affective responses varied based on disciplinary orientation. This may be influenced by the direct applicability of ChatGPT in technical and computational contexts. Although comparative studies by discipline are limited, existing research supports the notion that perception and usefulness of AI tools like ChatGPT differ based on field of study (Yilmaz et al., 2023). Engineering students perceive ChatGPT as a highly useful tool, which evokes positive emotions tied to efficient problem-solving and automation of tasks relevant to their future professions (Acosta et al., 2024; Saif et al., 2024). Their stronger emotional affinity reflects an instrumental view that underscores the importance of considering disciplinary context when analyzing attitudes toward emerging technologies.

Theoretically, this study contributes to the growing body of research in the Latin American context. The validation of the instrument based on Mitcham's (1994) philosophical framework confirms the applicability of a multidimensional understanding of technology—encompassing objective, knowledge, activity, and value dimensions. In this view, attitude is not merely a superficial response to tool usage but a multidimensional manifestation of how students understand, emotionally experience, and behaviorally engage with technologies that transform cognitive and educational practices during their academic formation. The three-component attitude structure (cognitive, affective, and behavioral) integrates technical knowledge with value judgments. Thus, this study not only provides a valid measurement model for attitudes toward ChatGPT but also a solid conceptual foundation for future research in emerging educational scenarios.

Practically, the findings offer valuable insights for guiding institutional policies, instructional strategies, and assessment approaches within higher education. Since no significant gender- or age-based differences were found, inclusive and cross-cutting integration strategies can be implemented without strict segmentation. However, the affective dimension—especially among engineering students—highlights the need to tailor technology implementation strategies to specific professional profiles. Universities are encouraged to promote differentiated initiatives by academic areas, fostering critical AI literacy that strengthens the connection between tool utility and the demands placed on 21st century professionals. Moreover, the validated instrument serves as a practical tool for diagnosing, monitoring, and optimizing student attitudes toward ChatGPT, enabling reflective, ethical, and pedagogically sound adoption of AI in education.

In conclusion, the findings of this study support the assertion that attitudes toward ChatGPT in the Peruvian university context are structured around three distinct components: cognitive, affective, and behavioral. Within this validated framework, comparative analyses revealed no significant differences in attitudes based on students' sex or age. This suggests a generalized perception of ChatGPT that transcends traditional demographic factors. However, when comparing academic disciplines, significant differences were observed only in the affective component—engineering students demonstrated greater emotional affinity toward ChatGPT compared to students in social/business sciences and natural sciences.

Although the study provides valuable insights, it also presents certain limitations. The use of a cross-sectional, non-experimental design prevents the establishment of causal relationships or the observation of changes in attitudes over time. Additionally, the sample was drawn exclusively from a single Peruvian university, which limits the generalizability of the findings to other cultural, educational, or geographical contexts. While the instrument was successfully validated within Mitcham's (1994) theoretical framework, the study focused only on sociodemographic variables such as sex, age, and academic faculty, excluding potentially influential factors such as level of proficiency, frequency of use, or personal beliefs regarding ethics and autonomy in learning. These limitations should be considered when designing future lines of research.

For future research, it is recommended to adopt longitudinal or mixed-method designs that allow for a deeper understanding of the evolution of attitudes toward ChatGPT over time and to establish stronger explanatory relationships. Expanding the sample to include various educational contexts—regional, national, and international—would allow researchers to identify potential cultural patterns. It is also important to incorporate new explanatory and moderating variables, such as students' experience with ChatGPT and the specific purposes for which they use the tool. Doing so would support the development of more comprehensive—and potentially predictive—models of attitudes in university settings. Finally, it is advisable to explore qualitative approaches that can capture the subjective dimension of students' experiences with ChatGPT, offering deeper insight into their perceptions and interactions with this emerging technology.

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REFERENCES

Acosta, B. G., Arbulú, C. G., Huamaní, O., Arbulú, M. A., & Paredes, A. E. (2024). Exploring attitudes toward ChatGPT among college students: An empirical analysis of cognitive, affective, and behavioral components using path analysis. *Computers and Education: Artificial Intelligence, 7*, Article 100320. https://doi.org/10.1016/j.caeai.2024.100320

Al Naqbi, H., Bahroun, Z., & Ahmed, V. (2024). Enhancing work productivity through generative artificial intelligence: A comprehensive literature review. *Sustainability, 16*(3), Article 1166. https://doi.org/10.3390/su16031166

Ali, D., Fatemi, Y., Boskabadi, E., Nikfar, M., Ugwuoke, J., & Ali, H. (2024). ChatGPT in teaching and learning: A systematic review. *Education Sciences, 14*(6), Article 643. https://doi.org/10.3390/educsci14060643

Almomani, J., & Alnasraween, M. (2024). Attitudes of gifted students in Jordan towards employing artificial intelligence and its applications in the educational process. *Journal of Umm Al-Qura University For Educational and Psychological Sciences, 16*(1), 69–78. https://doi.org/10.54940/ep18763271

Ankiewicz, P. (2019). Alignment of the traditional approach to perceptions and attitudes with Mitcham's philosophical framework of technology. *International Journal of Technology and Design Education, 29*(2), 329–340. https://doi.org/10.1007/s10798-018-9443-6

Ato, M., López-García, J. J., & Benavente, A. (2013). Un sistema de clasificación de los diseños de investigación en psicología [A classification system for research designs in psychology]. *Anales de Psicología, 29*(3), 1038–1059. https://doi.org/10.6018/analesps.29.3.178511

Beig, S., & Qasim, S. H. (2023). Assessing students' attitude towards artificial intelligence with respect to gender and use of computer and mobile devices. *International Journal for Multidisciplinary Research, 5*(3). https://doi.org/10.36948/ijfmr.2023.v05i03.4130

Bodani, N., Lal, A., Maqsood, A., Altamash, S., Ahmed, N., & Heboyan, A. (2023). Knowledge, attitude, and practices of general population toward utilizing ChatGPT: A cross-sectional study. *SAGE Open, 13*(4). https://doi.org/10.1177/21582440231211079

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research, 1*(2), 245–276. https://doi.org/10.1207/s15327906mbr0102_10

Chura-Quispe, G., Flores-Rosado, C. B., Valenzuela-Romero, A. A., Herrera-Pérez, E. I., Herrera-Chura, A. E., & Collazos Alarcón, M. A. (2025). Self-perceived information literacy skills in Peruvian university students: A metric and descriptive-comparative study. *Contemporary Educational Technology, 17*(1), Article ep560. https://doi.org/10.30935/cedtech/15776

Crompton, H., & Burke, D. (2024). The educational affordances and challenges of ChatGPT: State of the field. *TechTrends, 68*, 380–392. https://doi.org/10.1007/s11528-024-00939-0

Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education, 227*, Article 105224. https://doi.org/10.1016/j.compedu.2024.105224

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., & Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*. Harcourt Brace Jovanovich College Publishers.

Elkhatat, A. M. (2023). Evaluating the authenticity of ChatGPT responses: A study on text-matching capabilities. *International Journal for Educational Integrity, 19*, Article 15. https://doi.org/10.1007/s40979-023-00137-0

Estrada, E., Mamani, M., Quispe, J., Manrique, Y. V., & Cruz, E. O. (2025). Academic self-efficacy and dependence on artificial intelligence in a sample of university students. *Sapienza: International Journal of Interdisciplinary Studies, 6*(1), Article e25008. https://doi.org/10.51798/sijis.v6i1.916

Estrada, E., Paredes, Y., Quispe, R., Gallegos, N., Rivera, F., & Romaní, A. (2024). Investigating the attitude of university students towards the use of ChatGPT as a learning resource. *Data and Metadata, 3*, Article 268. https://doi.org/10.56294/dm2024268

Fajt, B., & Schiller, E. (2025). ChatGPT in academia: University students' attitudes towards the use of ChatGPT and plagiarism. *Journal of Academic Ethics, 23*, 1363–1382. https://doi.org/10.1007/s10805-025-09603-5

Farhi, F., Jeljeli, R., Aburezeq, I., Dweikat, F. F., Al-Shami, S. A., & Slamene, R. (2023). Analyzing the students' views, concerns, and perceived ethics about ChatGPT usage. *Computers and Education: Artificial Intelligence, 5*, Article 100180. https://doi.org/10.1016/j.caeai.2023.100180

García Castro, R. A., Chura-Quispe, G., Velarde Molina, J. F., Espinoza Ramos, L. A., & Almonte Durand, C. A. (2024). Bibliometric review on teaching methods with artificial intelligence in education. *Online Journal of Communication and Media Technologies, 14*(2), Article e202419. https://doi.org/10.30935/ojcmt/14367

Hadlington, L., Binder, J., Gardner, S., Karanika-Murray, M., & Knight, S. (2023). The use of artificial intelligence in a military context: Development of the attitudes toward AI in defense (AAID) scale. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1164810

Hasanein, A. M., & Sobaih, A. E. E. (2023). Drivers and consequences of ChatGPT use in higher education: Key stakeholder perspectives. *European Journal of Investigation in Health, Psychology and Education, 13*(11), 2599–2614. https://doi.org/10.3390/ejihpe13110181

Hassani, H., & Silva, E. S. (2023). The role of ChatGPT in data science: How AI-assisted conversational interfaces are revolutionizing the field. *Big Data and Cognitive Computing, 7*(2), Article 62. https://doi.org/10.3390/bdcc7020062

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Humr, S., Canan, M., & Demir, M. (2025). A quantum probability approach to improving human–AI decision making. *Entropy, 27*(2), Article 152. https://doi.org/10.3390/e27020152

Isiaku, L., Muhammad, A. S., Kefas, H. I., & Ukaegbu, F. C. (2024). Enhancing technological sustainability in academia: Leveraging ChatGPT for teaching, learning, and evaluation. *Quality Education for All, 1*(1), 385–416. https://doi.org/10.1108/qea-07-2024-0055

Karafil, B., & Uyar, A. (2025). Exploring knowledge, attitudes, and practices of academics in the field of educational sciences towards using ChatGPT. *Education and Information Technologies, 30*, 11649–11692. https://doi.org/10.1007/s10639-024-13291-w

Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update, 5*, Article 100145. https://doi.org/10.1016/j.cmpbup.2024.100145

Kleib, M., Darko, E. M., Akingbade, O., Kennedy, M., Majekodunmi, P., Nickel, E., & Vogelsang, L. (2024). Current trends and future implications in the utilization of ChatGPT in nursing: A rapid review. *International Journal of Nursing Studies Advances, 7*, Article 100252. https://doi.org/10.1016/j.ijnsa.2024.100252

Köse, N., Şimşek, E., & Demir, M. C. (2025). Adaptation of artificial intelligence attitude scale (AIAS-4) into Turkish: A validity and reliability study. *Current Psychology, 44*, 8096–8105. https://doi.org/10.1007/s12144-025-07418-6

Kovačević, A., & Demić, E. (2024). The impact of gender, seniority, knowledge, and interest on attitudes to artificial intelligence. *IEEE Access, 12*, 129765–129775. https://doi.org/10.1109/ACCESS.2024.3454801

Kovari, A. (2025). Ethical use of ChatGPT in education–Best practices to combat AI-induced plagiarism. *Frontiers in Education, 9*. https://doi.org/10.3389/feduc.2024.1465703

Laizure, S. C. (2024). Caution: ChatGPT doesn't know what you are asking and doesn't know what it is saying. *The Journal of Pediatric Pharmacology and Therapeutics, 29*(5), 558–560. https://doi.org/10.5863/1551-6776-29.5.558

Li, C. (2015). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods, 48*(3), 936–949. https://doi.org/10.3758/s13428-015-0619-7

Liu, J. (2024). ChatGPT: Perspectives from human-computer interaction and psychology. *Frontiers in Artificial Intelligence, 7*. https://doi.org/10.3389/frai.2024.1418869

Marengo, A., Karaoglan-Yilmaz, F. G., Yılmaz, R., & Ceylan, M. (2025). Development and validation of generative artificial intelligence attitude scale for students. *Frontiers in Computer Science, 7*. https://doi.org/10.3389/fcomp.2025.1528455

Memarian, B., & Doleck, T. (2023). ChatGPT in education: Methods, potentials, and limitations. *Computers in Human Behavior: Artificial Humans, 1*(2), Article 100022. https://doi.org/10.1016/j.chbah.2023.100022

Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to use OpenAI's ChatGPT using the UTAUT model. *Heliyon, 9*(11), Article e20962. https://doi.org/10.1016/j.heliyon.2023.e20962

Mitcham, C. (1994). *Thinking through technology: The path between engineering and philosophy*. University of Chicago Press.

Mondal, H., & Mondal, S. (2023). ChatGPT in academic writing: Maximizing its benefits and minimizing the risks. *Indian Journal of Ophthalmology, 71*(12), 3600–3606. https://doi.org/10.4103/IJO.IJO_718_23

Naznin, K., Al Mahmud, A., Nguyen, M. T., & Chua, C. (2025). ChatGPT integration in higher education for personalized learning, academic writing, and coding tasks: A systematic review. *Computers, 14*(2), Article 53. https://doi.org/10.3390/computers14020053

Oates, A., & Johnson, D. (2025). ChatGPT in the classroom: Evaluating its role in fostering critical evaluation skills. *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-024-00452-8

Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. *Applied Sciences, 13*(9), Article 5783. https://doi.org/10.3390/app13095783

Raj, R., Singh, A., Kumar, V., & Verma, P. (2023). Analyzing the potential benefits and use cases of ChatGPT as a tool for improving the efficiency and effectiveness of business operations. *BenchCouncil Transactions on Benchmarks, Standards and Evaluations, 3*(3), Article 100140. https://doi.org/10.1016/j.tbench.2023.100140

Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems, 3*, 121–154. https://doi.org/10.1016/j.iotcps.2023.04.003

Romero-Rodríguez, J., Ramírez-Montoya, M., Buenestado-Fernández, M., & Lara-Lara, F. (2023). Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness. *Journal of New Approaches in Educational Research, 12*(2), 323–339. https://doi.org/10.7821/naer.2023.7.1458

Roumeliotis, K. I., & Tselikas, N. D. (2023). ChatGPT and Open-AI models: A preliminary review. *Future Internet, 15*(6), Article 192. https://doi.org/10.3390/fi15060192

Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). Chat-GPT: Validating technology acceptance model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior, 154*, Article 108097. https://doi.org/10.1016/j.chb.2023.108097

Schepman, A., & Rodway, P. (2022). The general attitudes towards artificial intelligence scale (GAAIS): Confirmatory validation and associations with personality, corporate distrust, and general trust. *International Journal of Human-Computer Interaction, 39*(13), 2724–2741. https://doi.org/10.1080/10447318.2022.2085400

Seo, Y. H., & Ahn, J. (2022). The validity and reliability of the Korean version of the general attitudes towards artificial intelligence scale for nursing students. *The Journal of Korean Academic Society of Nursing Education, 28*(4), 357–367. https://doi.org/10.5977/jkasne.2022.28.4.357

Sindermann, C., Sha, P., Zhou, M., Wernicke, J., Schmitt, H. S., Li, M., Sariyska, R., Stavrou, M., Becker, B., & Montag, C. (2020). Assessing the attitude towards artificial intelligence: Introduction of a short measure in German, Chinese, and English language. *KI–Künstliche Intelligenz, 35*(1), 109–118. https://doi.org/10.1007/s13218-020-00689-0

Smith, P., & Smith, L. (2024). This season's artificial intelligence (AI): Is today's AI really that different from the AI of the past? Some reflections and thoughts. *AI Ethics, 4*(4), 665–668. https://doi.org/10.1007/s43681-023-00388-0

Stein, J., Messingschlager, T., Gnambs, T., Hutmacher, F., & Appel, M. (2024). Attitudes towards AI: measurement and associations with personality. *Scientific Reports, 14*(1). https://doi.org/10.1038/s41598-024-53335-2

Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *SAGE Open, 12*(2). https://doi.org/10.1177/21582440221100463

Suriano, R., Plebe, A., Acciai, A., & Fabio, R. A. (2025). Student interaction with ChatGPT can promote complex critical thinking skills. *Learning and Instruction, 95*, Article 102011. https://doi.org/10.1016/j.learninstruc.2024.102011

Svenningsson, J. (2020). The Mitcham score: Quantifying students' descriptions of technology. *International Journal of Technology and Design Education, 30*, 995–1014. https://doi.org/10.1007/s10798-019-09530-8

Tien, L. M. (2024). Exploring undergraduate students' general attitudes towards Artificial Intelligence: A perspective from Vietnam. *Journal of Language and Cultural Education, 12*(3), 16–22. https://doi.org/10.2478/jolace-2024-0014

Ventura-León, J. L. (2017). Intervalos de confianza para coeficiente omega: Propuesta para el cálculo [Confidence intervals for omega coefficient: Proposal for calculation]. *Adicciones, 30*(1), 77–78. https://doi.org/10.20882/adicciones.962

von Garrel, J., & Mayer, J. (2023). Artificial intelligence in studies–Use of ChatGPT and AI-based tools among students in Germany. *Humanities and Social Sciences Communications, 10*, Article 799. https://doi.org/10.1057/s41599-023-02304-7

Xia, Y., & Yang, Y. (2018). The influence of number of categories and threshold values on fit indices in structural equation modeling with ordered categorical data. *Multivariate Behavioral Research, 53*(5), 731–755. https://doi.org/10.1080/00273171.2018.1480346

Yılmaz, D., Uzelli, D., & Dikmen, Y. (2025). Psychometrics of the attitude scale towards the use of artificial intelligence technologies in nursing. *BMC Nursing, 24*(1). https://doi.org/10.1186/s12912-025-02732-7

Yilmaz, H., Maxutov, S., Baitekov, A., & Balta, N. (2023). Student attitudes towards ChatGPT: A technology acceptance model survey. *International Educational Review, 1*(1), 57–83. https://doi.org/10.58693/ier.114

Yu, S., Huang, Y., & Wu, T. (2024). Tool, threat, tutor, talk, and trend: College students' attitudes toward ChatGPT. *Behavioral Sciences, 14*(9), Article 755. https://doi.org/10.3390/bs14090755