

Exploring attitudes toward ChatGPT among college students: An empirical analysis of cognitive, affective, and behavioral components using path analysis

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ABSTRACT

The advent of generative artificial intelligence (AI) applications, such as ChatGPT, has significantly impacted various aspects of human life, including higher education. This study explores university students' attitudes toward ChatGPT, focusing on the cognitive, affective, and behavioral components of attitudes, on the basis of Mitcham's philosophical framework of attitudes toward technology. A total of 595 university students from six public and private universities in northern Peru participated in an online survey. The results of the structural equation modeling (SEM) analysis revealed that the affective component ($\beta = 0.672^{***}$) and the cognitive component ($\beta = 0.260^{**}$) positively influence the behavioral component of students' attitudes when ChatGPT is used. Moreover, the cognitive component ($\beta = 0.931^{***}$) positively influences the affective component of students' attitudes. However, gender and age did not have significant moderating effects on the relationships between the cognitive and affective components and the behavioral component. The discussion highlights that these findings contribute to understanding the psychological mechanisms underlying the adoption of ChatGPT in educational settings and offer valuable guidance for implementing this technology in teaching and learning processes. In conclusion, this study represents a significant advancement in comprehending attitudes toward generative AI technologies in higher education and opens new avenues for future research in this field.

1. Introduction

Generative artificial intelligence applications, such as ChatGPT, significantly impact various aspects of human life. ChatGPT, developed by OpenAI, is a highly advanced AI chatbot that uses deep learning techniques to generate text in natural language (Choi et al., 2023). In terms of user engagement, ChatGPT reached a milestone of 100 million monthly active users within a two-month period (Hu, 2023). ChatGPT has been trained on an extensive array of online textual data, including journalistic articles, books, and web pages, enabling it to handle a wide range of requests—from questions and statements to data retrieval (Graf & Bernardi, 2023; Kasneci et al., 2023).

ChatGPT has been finely tuned with extensive data to understand

and interpret user queries with high accuracy, establishing it as an advanced tool for natural language processing (NLP) driven by artificial intelligence (Perez-Castro et al., 2023; Thorp, 2023). Its ability to generate text mimicking human language proves invaluable for various writing applications, such as essay creation, narratives, marketing materials, and literature summaries (Duong et al., 2023; Patel & Lam, 2023).

In the context of higher education, the use of generative AI applications has been explored in various ways. Researchers have investigated their potential in developing new student-centered curricula that promote innovation and creativity (Farhi et al., 2023; Squalli Houssaini et al., 2024). Additionally, there is a recognized need to prepare students and educators for employment in a society enhanced by generative AI,

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with new learning outcomes such as AI literacy and an emphasis on interdisciplinarity and activity-based assessment (Chiu, 2024).

Several studies have demonstrated the positive impacts of ChatGPT in academic settings. Research has shown that ChatGPT can significantly improve the academic writing skills of university students who are nonnative English speakers (Mahapatra, 2024) and enhance the academic performance of business students by positively impacting their motivation, self-efficacy, and future beliefs (Gao et al., 2024). Furthermore, a randomized experiment with university students demonstrated that using ChatGPT improved self-efficacy, quality, elaboration, and originality in a complex creative problem-solving task (Urban et al., 2024).

However, the integration of ChatGPT in higher education also presents significant challenges. Concerns related to academic integrity and the detection of AI-generated texts have emerged. One study indicated that both novice and experienced teachers struggle to identify texts generated by ChatGPT among those written by students (Fleckenstein et al., 2024). Additionally, a study at a prominent Australian university revealed a lack of consensus and significant ambiguity among faculty regarding best practices in light of recent technological developments (Lee et al., 2024).

Ethical considerations surrounding the use of ChatGPT in academic settings have also been raised. Since artificial intelligence has the potential to replace many jobs, using it to write essays presents ethical and cheating concerns (Liebrenz et al., 2023; Tili et al., 2023). As a result, various educational institutions forbade ChatGPTs on their platforms and devices in 2023, and numerous higher education institutions released statements that caution students against using ChatGPTs for academic purposes (Camilleri, 2024).

Given the complex landscape of ChatGPT's integration in higher education, understanding students' attitudes toward this technology becomes crucial. Ajzen (2001) defines attitude as an assessment of a psychological object, which is delineated by dimensions such as agreeable versus disagreeable, pleasurable versus unpleasant, or good versus bad. Traditionally, attitudes are often divided into three different components: affective, cognitive, and behavioral (Breckler, 1984; Fishbein & Ajzen, 1975; Svenningsson et al., 2022).

Recent studies have begun to explore university students' attitudes toward ChatGPT. The attitudes of university students toward ChatGPT are generally positive across cognitive, affective, and behavioral components, with high utilization and favorable opinions about its educational benefits (Ajlouni et al., 2023). Previous studies have suggested that university students generally have positive perceptions of ChatGPT as a valuable resource for supporting their learning and enhancing their skills (Gao et al., 2024; Mahapatra, 2024).

Factors influencing students' adoption of ChatGPT have also been investigated. It has been reported that behavioral intention has the most significant effect (0.424) on usage behavior, followed by habits (0.255) and facilitating conditions (0.188) (Strzelecki, 2023). Additionally, there is a positive correlation between these perceptions and the acceptance of ChatGPT by students, indicating that their overall attitude toward the tool is likely to be positive if they find ChatGPT to be simple to use and beneficial (Albayati, 2024).

However, potential negative effects of excessive or inappropriate use of ChatGPT have also been identified. These include procrastination, memory loss, and decreased academic performance (Abbas et al., 2024). Concerns related to misinformation, technological unemployment, and the relationship between humans and computers have been noted (Lian et al., 2024).

A recent study by Acosta-Enriquez et al. (2024) evaluated the attitudes of university students toward ChatGPT and determined that importance, ease of use, risk, interest, boredom, positive emotions, and acceptance influence their intention to use, verify information, and responsibly use this language model. This study demonstrated that the cognitive and affective components determine the behavioral component of university students' attitudes toward ChatGPT.

Despite these insights, further research is necessary to fully understand the attitudes of students toward ChatGPT and how these attitudes may influence their use of this language model. Few studies have analyzed attitudes toward ChatGPT from the perspective of current psychological theory, where the cognitive, affective, and behavioral components establish relationships that determine the use of ChatGPT among university students.

This study aims to address this gap by providing valuable information on attitudes toward ChatGPT and can aid in the design of more effective educational interventions and policies that ethically regulate the use of artificial intelligence in academic settings. Integrating the theory of attitudes into the study of generative AI technology offers a robust framework for understanding how students' perceptions and behaviors are shaped by their cognitive and affective experiences. By examining these dimensions more deeply, educators and developers can create strategies that promote a more conscious and responsible use of these tools.

The primary goal of this study is to analyze attitudes toward ChatGPT from the perspective of the cognitive, affective, and behavioral components among university students in northern Peru. To achieve this objective, we designed a structural equation model (SEM) to analyze attitudes toward ChatGPT on the basis of Mitcham's philosophical framework of attitudes toward technology (Mitcham, 1994; Svenningsson et al., 2022).

This study is justified given the growing interest in understanding how emerging technologies such as ChatGPT impact education and prepare students for the demands of the workforce. For this reason, this study aims to evaluate attitudes toward ChatGPT among university students, the linguistic model of which has been widely accepted.

In terms of theoretical contributions, this study proposes providing empirical evidence of the relationships between the components of attitudes toward technology within the philosophical framework of Mitcham, distinguishing between technology as an object and technology as an activity. This approach will enable the unraveling not only of the perception of technology itself (cognitive component) but also of the emotional interaction with it (affective component) and its influence on behavior (behavioral component). Finally, the study seeks to provide evidence-based recommendations for educators and technology education designers on how to maximize the benefits of these tools while minimizing associated risks, such as technological dependency and challenges to academic integrity. By analyzing the dimensions of attitudes (cognitive, affective, and behavioral), this study contributes significantly to the field of educational technology in terms of the interaction between university students and generative artificial intelligence technologies and their impact on higher education.

2. Literature review

2.1. General implications of the ChatGPT

ChatGPT has been popularized and extensively adopted since its launch in November 2022, primarily because of its user-friendly interface and capacity to produce responses that resemble those of a human person. ChatGPT was developed via an instruction-based learning approach to generate more coherent responses that are aligned with user intentions, leveraging advancements in deep learning and natural language processing (Sleiman et al., 2022).

ChatGPT has evolved through several iterations, each with an increasing number of parameters: ChatGPT-1 utilized 117 million parameters, ChatGPT-2 expanded to 1.5 billion parameters, ChatGPT-3 further increased to 175 billion parameters, and the latest version, ChatGPT-4, incorporates an estimated 100 trillion parameters. This progression demonstrates the rapid advancements in the model's complexity and potential capabilities. To generate texts that closely resemble human speech and accomplish unprecedented performance levels, ChatGPT-4 has been able to enhance its parameters (Albayati,

2024; OpenAI et al., 2024).

At present, the GPT-3.5 version is a freely accessible language model that has been optimized for dialog via reinforcement learning with human feedback (OpenAI, 2023). This makes it more accessible to university students, who can readily access it by creating an account. The GPT-3.5 database was most recently updated in September 2021 (Qureshi et al., 2023). Conversely, the GPT-4.0 version, which is more creative than its predecessor and requires a paid subscription, has the ability to process images, create captions, perform classifications, and conduct analyses (Camilleri, 2024; Qureshi et al., 2023).

In the realm of higher education, ChatGPT has several potential benefits, such as assisting in the development of student-centered curricula that foster innovation and creativity (Squalli Houssaini et al., 2024), enhancing students' academic writing skills (Mahapatra, 2024), and fostering creative problem solving (Urban et al., 2024). Moreover, ChatGPT has the potential to transform higher education by offering benefits such as increased student motivation and engagement (Rahman et al., 2023), as well as personalized and enriched learning experiences (Chiu, 2024; Kanabar, 2023; Kong et al., 2023). ChatGPT can be a valuable tool to complement teaching and learning, enabling students to acquire new skills and knowledge more effectively. Intrinsic motivation is highlighted as a key factor in the intention to use ChatGPT among university students (Lai et al., 2023).

However, the implementation of ChatGPT in higher education also presents significant challenges that need to be addressed. There is concern that students may become overly dependent on the tool or use it in unethical ways, which could affect the development of critical thinking skills and academic integrity (Ali et al., 2023; Fleckenstein et al., 2024). Additionally, challenges such as the difficulty in detecting AI-generated texts (Fleckenstein et al., 2024), the lack of consensus on best practices for their use (Lee et al., 2024), and the potential negative effects of excessive or inappropriate use by students, such as procrastination and memory loss (Abbas et al., 2024), need to be considered. Furthermore, the ethical and legal implications of using AI in fields such as healthcare must be carefully considered (Aljamaan et al., 2024; Bernabei et al., 2023; Kanabar, 2023; Sallam et al., 2023).

2.2. Attitudinal components of Mitcham's philosophical framework

2.2.1. Overview of Mitcham's framework

Mitcham's philosophical framework of technology, encompassing objects, knowledge, activity, and volition, has been widely recognized as a significant contribution to the philosophy of technology (Mitcham, 1994). This multidimensional approach provides a solid foundation for analyzing the complex interactions between technology and humanity, particularly in educational contexts.

Fig. 1 shows a graphical representation of Mitcham's philosophical framework applied to the attitudinal components toward technology. This model shows the interrelationships among the cognitive, affective,

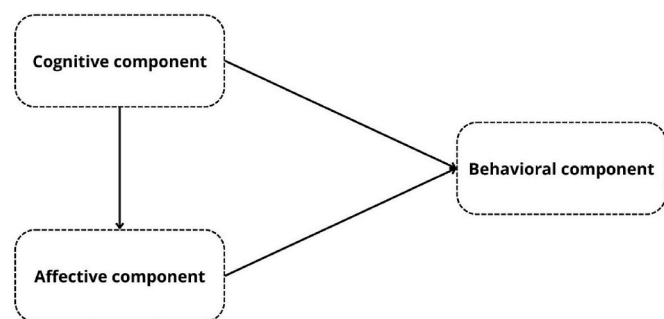


Fig. 1. Graphical representation of Mitcham's philosophical framework applied to the attitudinal components toward technology. Adapted from (Svenningsson et al., 2022).

and behavioral components, which form the basis of our study of attitudes toward ChatGPT.

In Mitcham's framework, technology is conceptualized not only as physical objects but also as a form of knowledge, a type of activity, and an expression of human will or volition. This comprehensive view allows for a nuanced understanding of how individuals perceive, feel about, and interact with technology.

Building on Mitcham's framework, researchers have identified three distinct components of attitudes toward technology: cognitive, affective, and behavioral (Breckler, 1984; Eagly & Chaiken, 1993, p. xxii; Fishbein & Ajzen, 1975). These components align with Mitcham's multidimensional approach to technology.

1. **Cognitive Component:** This component relates to Mitcham's concepts of technology as knowledge and objects. It encompasses an individual's beliefs, thoughts, and perceptions about technology (Schepman & Rodway, 2020; Svenningsson et al., 2022). In the context of ChatGPT, this might include beliefs about its usefulness or complexity.
2. **Affective Component:** This aligns with Mitcham's notion of volition, reflecting an individual's emotional responses to technology. It includes feelings, whether favorable or unfavorable, toward technology (Suh & Ahn, 2022; Svenningsson et al., 2022). For ChatGPT, this could involve feelings of excitement or apprehension about its use.
3. **Behavioral Component:** This component corresponds to Mitcham's concept of technology as an activity. It refers to observable actions or behaviors exhibited in response to technology, such as adoption, continued use, or rejection (Ankiewicz, 2019; Svenningsson et al., 2022). In the case of ChatGPT, this might manifest as the frequency of use or ways of integrating it into academic work.

2.2.2. Literature review on the attitudinal components of technology acceptance

The relationships among the cognitive, affective, and behavioral components, as formulated in Mitcham's framework and illustrated in Fig. 1, form the basis of our research hypotheses: the cognitive component (CC) influences the affective component (AC); the cognitive component (CC) influences the behavioral component (BC); and the affective component (AC) influences the behavioral component (BC) (Svenningsson et al., 2022).

Studies applying this framework in educational contexts have demonstrated its effectiveness in linking these attitudinal components with technology, highlighting how they influence each other and differ according to factors such as gender (Ankiewicz, 2019; Svenningsson et al., 2022). In addition to its application in higher education, Mitcham's conceptual framework has generated more nuanced debates about the epistemological dimensions of technology and engineering, acting as a bridge that connects engineering and humanities perspectives in the philosophy of technology (Svenningsson et al., 2018).

Recent studies have provided insights into attitudes toward AI technologies such as ChatGPT in educational settings. Acosta-Enriquez et al. (2024) demonstrated that positive emotions and the intention to use ChatGPT are frequently significant predictors of positive attitudes among college students. This finding aligns with the affective and behavioral components of Mitcham's framework, emphasizing the connection between emotional responses and intended actions.

The cognitive component plays a crucial role in shaping attitudes toward ChatGPT. Abdaljeel et al. (2024) reported that factors such as awareness and alertness significantly impact attitudes toward ChatGPT among university students. This underscores the importance of the cognitive aspect in Mitcham's framework, where knowledge and understanding of technology influence overall attitudes.

Zhang et al. (2024) reported a pattern of cautious optimism among university students toward the ChatGPT. This nuanced attitude reflects a balance between enthusiasm and a rational assessment of potential risks, illustrating the complex interplay between the cognitive and affective

components in Mitcham's framework.

The social context also influences attitude formation. [Sánchez-Reina et al. \(2024\)](#) explored how social influence affects undergraduates' attitudes toward ChatGPT, suggesting that technology acceptance is determined not only by individual perceptions but also by broader social factors. This finding adds depth to Mitcham's framework, emphasizing the need to consider external influences on attitude formation.

However, attitudes toward AI technologies such as ChatGPT are not uniformly positive. [Schönberger \(2023, pp. 331–338\)](#) and [Sedlbauer et al. \(2024\)](#) noted that some educators and students expressed concerns about the ethical implications and potential misuse of AI technologies in academic settings. These cautious attitudes highlight the importance of considering ethical dimensions within Mitcham's framework, particularly in the context of emerging technologies.

The review of scholarly articles that cite this framework underscores its adaptability and fundamental role in enhancing our understanding of the philosophical, educational, and social dimensions of technology, thus establishing a solid basis for the study of attitudinal components toward technology in various contexts ([Ankiewicz, 2019](#); [Svenningsson et al., 2022](#)).

By applying Mitcham's framework to ChatGPT, this study aims to connect philosophical conceptualizations of technology with practical applications in educational settings. This research advances the understanding of university students' attitudes toward ChatGPT by analyzing these intercomponent influences. Unlike previous studies (e.g., [Rahman et al., 2023](#); [Masa'deh et al., 2024](#); [Acosta-Enriquez et al., 2024](#)), this study provides empirical evidence of how these components influence each other, elucidating how college students adopt a new technology such as ChatGPT.

3. Proposed research model and formulation of the research hypotheses

[Fig. 2](#) presents the proposed research model, which consists of three components of attitudes (cognitive, affective, and behavioral) and two sociodemographic variables: gender and age. The model is grounded in Mitcham's philosophical framework on attitudes toward technology ([Mitcham, 1994](#); [Svenningsson, 2020](#); [Svenningsson et al., 2018, 2022](#)) and involves three direct hypotheses and four moderation hypotheses.

Perceived usefulness (PU) and perceived informativeness, which are cognitive components, significantly influence students' attitudes toward using ChatGPT for learning, subsequently predicting their behavioral intention to use it ([Rahman et al., 2023](#)). PU is an important factor influencing students' attitudes and behavioral intentions toward

ChatGPT ([Masa'deh et al., 2024](#); [Duong et al., 2023](#); [Strzelecki, 2023](#)). These findings align with research in technology education, where individual interest (affective component) relates to the cognitive component and behavioral intentions, particularly in girls ([Svenningsson et al., 2022](#)).

Although affect tends to exert a stronger influence than cognition does on overall attitudes and behavior when individuals exhibit affective-cognitive ambivalence, cognition has a roughly equal influence when affect and cognition are similarly valenced ([Lavine et al., 1998](#)). In STEM fields, social support can directly affect both cognitive and affective components, leading to more positive attitudes ([Rice et al., 2013](#)). [Brown et al. \(2017\)](#) showed that cognitive and affective components can be distinctly measured and that these attitudes can vary across different courses, implying that the cognitive component impacts the affective attitude. Consequently, it can be inferred that the cognitive component positively influences the affective component of attitudes toward ChatGPT among university students. Thus, the following hypothesis is formulated.

Hypothesis 1. The cognitive component positively influences the affective component of attitudes toward ChatGPT among university students.

The influence of the cognitive component on the behavioral component of attitudes toward ChatGPT has been demonstrated in several studies. Perceived usefulness has a significant positive effect on students' behavioral intention to use ChatGPT ([Duong et al., 2023](#); [Masa'deh et al., 2024](#); [Strzelecki, 2023](#)). [Rahman et al. \(2023\)](#) reported that perceived usefulness and informativeness substantially influence students' attitudes toward using ChatGPT for learning, thus predicting their behavioral intentions. These findings align with research in technology education, where the cognitive component directly relates to behavioral intentions, particularly among girls ([Svenningsson et al., 2022](#)). Cognitive strategies are strong predictors of academic achievement, indicating that cognitive aspects significantly influence students' behaviors in educational contexts ([Peng, 2012](#)). Social factors can moderate the impact of cognitive beliefs on behavioral outcomes, as evidenced by the relationship between cognitive attitudes toward math and science and behavioral intentions to pursue STEM courses and careers ([Rice et al., 2013](#)). Thus, the following hypothesis is developed.

Hypothesis 2. The cognitive component positively influences the behavioral component of attitudes toward ChatGPT among university students.

Recent studies have explored the influence of the affective component on the behavioral component of attitudes toward ChatGPT. [Lai et al. \(2023\)](#) identified intrinsic motivation as the strongest motivator for ChatGPT use intention among undergraduates. [Masa'deh et al., \(2024\)](#) reported that enjoyment and motivation contribute to a favorable attitude toward using ChatGPT in learning environments. Students exhibit a positive affective attitude toward ChatGPT, which is associated with a high level of behavioral intention to use it as a learning tool ([Ajilouni et al., 2023](#)). A positive emotional response toward ChatGPT correlates with actual usage ([Hyeon Jo, 2023](#)). Affective attitudes toward academic subjects, including technology, can vary over time and may influence cognitive attitudes, which could affect behavioral intentions ([Brown et al., 2017](#)). Thus, the following hypothesis is developed.

Hypothesis 3. The affective component positively influences the behavioral component of attitudes toward ChatGPT among university students.

Recent studies have examined how gender and age moderate the impact of cognitive and affective components on the behavioral component of attitudes toward ChatGPT. [Strzelecki and ElArabawy \(2024\)](#) reported that gender does not substantially influence the relationships between various factors and the behavioral intention to use

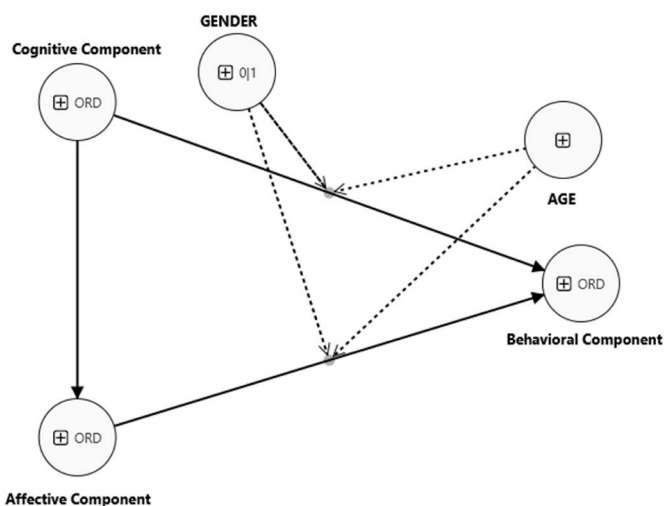


Fig. 2. Proposed research model. Note: Cognitive Component = CC, Affective Component = AC, Behavioral Component: BC.

ChatGPT. However, the level of study moderated the impact of effort expectations on behavioral intentions.

Previous research on attitudes toward computers has shown that age and experience, rather than gender, significantly affect attitudes (Pope-Davis & Twing, 1991). However, female university students show greater adherence to cognitive learning strategies than their male counterparts do (Kesici et al., 2009). The internal locus of control is a significant factor in cognitive learning strategies and attitudes toward computers among university students (Kesici et al., 2009).

Older female students achieved greater deep learning and satisfaction with their profession (Rubin et al., 2018), suggesting that older women may engage more thoroughly with technologies such as ChatGPT when they perceive a deeper learning experience. Gender may affect how cognitive and affective components influence behavioral intentions toward educational technologies (Kesici et al., 2009). Age-related differences in emotional intelligence and social and academic adjustment could influence behavioral intentions to adopt new technologies for academic purposes (Noor-Azniza et al., 2011). Age was a stronger predictor of deep learning among women than men in the context of emotional intelligence and learning approaches (Rubin et al., 2018).

Recent studies have further explored the roles and impacts of ChatGPT in educational contexts. Lai and Tu (2024) investigated the roles, strategies, and research issues of generative AI in mobile learning, providing insights into how ChatGPT might be integrated into diverse learning environments. Tu and Hwang (2023) examined university students' conceptions of ChatGPT-supported learning through drawing and epistemic network analysis, offering a unique perspective on how students perceive and conceptualize this technology. Chang and Hwang (2024) explored ChatGPT-facilitated professional development, focusing on learning achievements, self-worth, and self-confidence among professional trainers. Tu (2024) investigated the roles and functionalities of ChatGPT for students with different growth mindsets, highlighting the importance of individual differences in technology adoption.

This study aims to explore how gender and age may moderate the influence of cognitive and affective components on the behavioral component of attitudes toward ChatGPT among university students. By examining these demographic factors in relation to the attitudinal components of ChatGPT, this study seeks to provide a more nuanced understanding of how individual characteristics can shape perceptions and use of this generative AI technology in educational contexts. Consequently, the following hypotheses are formulated.

Hypothesis 4. Gender moderates the influence of the cognitive component on the behavioral component of attitudes toward ChatGPT among university students.

Hypothesis 5. Gender moderates the influence of the affective component on the behavioral component of attitudes toward ChatGPT among university students.

Hypothesis 6. Age moderates the influence of the cognitive component on the behavioral component of attitudes toward ChatGPT among university students.

Hypothesis 7. Age moderates the influence of the affective component on the behavioral component of attitudes toward ChatGPT among university students.

4. Methods and materials

To test the research hypotheses, an empirical evaluation was conducted (Singh et al., 2020), in which a survey was administered to university students with experience using ChatGPT.

4.1. Participants

The study involved the participation of 595 university students from six public and private universities located in northern Peru. The sample was chosen by nonprobability convenience sampling, which entailed selecting people who were readily accessible and willing to engage willingly (Arrogante, 2022). This sampling strategy is appropriate for the study because it enables rapid and efficient data collection in situations where limited accessibility and the desire to participate can impose constraints. While this strategy cannot ensure that the sample is representative of the entire university population, it is valuable in exploratory research where the main goal is to find first trends and patterns rather than make sweeping generalizations. Nevertheless, the lack of representativeness of the sample in this study hinders the capacity to extrapolate the findings to the broader population. The statistical power may be compromised, as the findings from this sample fail to accurately represent the actual characteristics of the university student population in Peru. According to Table 1, 54.62% (325 participants) of the total university students surveyed were female, and 45.37% (270 participants) were male. In terms of age, 31.42% (187 participants) were in the 21- to 23-year-old age range, followed by 22.51% (134 participants) in the 18- to 20-year-old age range. Additionally, the data reveal an almost equal distribution in terms of the type of university, with 50.420% (300 participants) attending public universities and 49.580% (295 participants) attending private universities.

With respect to the faculty of study, the majority of the students belonged to the faculty of education, with 31.76% (189 participants). This group was followed by students from the social sciences, who accounted for 16.63% (99 participants) of the sample. Notably, all the respondents indicated that they had prior experience using ChatGPT in the university context, which reflects a total integration of this technology in their academic environment.

Table 1
Sociodemographic characteristics of the sample (n = 595).

Gender	fi	%
Female	325	54.62
Male	270	45.37
Age	fi	%
[18–20]	134	22.51
[21–23]	187	31.42
[24–26]	89	14.95
[27–29]	78	13.10
[30–32]	63	10.58
[33 to more]	44	7.40
Type of university	fi	%
Private	295	49.580
Public	300	50.420
Faculty of studies	fi	%
Education	189	31.76
Health sciences and medicine	67	11.26
Engineering and architecture	56	9.41
Social sciences	99	16.63
Business sciences	32	5.38
Law and political science	45	7.56
Economics and accounting	24	4.03
Agricultural Sciences	33	5.54
Physical sciences, mathematics, statistics, and computer science	50	8.40
Do you have previous experience using ChatGPT at the university?	fi	%
Yes	595	100.0
No	0	0

Note: fi = absolute frequency; % = percentage.

4.2. Instruments

To select the data collection instrument used in the literature, a review of the literature was conducted, which helped identify the

cognitive, affective, and behavioral components of attitudes toward technology, grounded in Mitcham's philosophical framework (Mitcham, 1994; Svenningsson et al., 2022). Furthermore, for the drafting of the items, an adaptation of the validated instrument authored by

Table 2
Results of the confirmatory factor analysis-CFA.

Items		Loadings	DE	AVE	Construct	Support
I am willing to use ChatGPT as a tool to improve my academic performance.	BC1	0.888	1.424	0.696	Behavioral Component (BC)	Suh and Ahn (2022)
I am willing to use ChatGPT as part of my learning process at university.	BC2	0.898	1.361			
I am open to use ChatGPT as part of my learning process at university.	BC3	0.898	1.393		Affective Component (AC)	(Suh & Ahn, 2022; Svenningsson et al., 2022)
I prefer to use ChatGPT as a complementary tool in my academic activities.	AC1	0.913	1.457	0.763		
I am attracted to the possibility of using ChatGPT to improve my academic productivity and efficiency.	AC2	0.844	1.427			
I feel enthusiastic about using ChatGPT to seek solutions and answers to my academic concerns.	AC3	0.736	1.457			
I find using ChatGPT in my academic activities boring.	AC4	0.854	1.349			
ChatGPT offers practical and useful solutions to academic and/or personal challenges and tasks.	AC5	0.895	1.348			
ChatGPT is a useful tool to understand and comprehend complex topics in my courses.	AC6	0.897	1.319			
Using ChatGPT in my academic activities is important because it enhances my learning experience.	CC1	0.84	1.387	0.721	Cognitive Component (CC)	(Singh et al., 2020; Svenningsson et al., 2022)
ChatGPT improves my productivity and efficiency in performing academic activities.	CC2	0.858	1.381			
Using ChatGPT in my academic activities contributes to the efficiency and effectiveness of my learning process.	CC3	0.873	1.298			
ChatGPT is a tool that enhances my ability to develop academic projects and activities.	CC4	0.854	1.352			
ChatGPT interface is user-friendly and easy to use.	CC5	0.882	1.401			
I find it difficult to tailor ChatGPT responses to my specific academic needs.	CC6	0.891	1.433			
I find it difficult to filter relevant information from the answers generated by ChatGPT.	CC7	0.887	1.456			
Using ChatGPT in my academic activities allows me to develop complex projects and tasks more efficiently and effectively.	CC8	0.882	1.452			
Artificial intelligence systems like ChatGPT can help students feel happier.	AC7	0.903	1.373	0.763	Affective Component (AC)	Schepman and Rodway (2020)
I am impressed by what I can do using ChatGPT in my academic activities.	AC8	0.907	1.382			
I believe that ChatGPT can have positive effects on students' well-being.	AC9	0.892	1.392			
I dislike the idea that technology such as ChatGPT replaces certain human skills such as inferring, information seeking, analyzing, writing, etc.	AC10	0.862	1.342			
I will use ChatGPT frequently in my academic activities over a long period of time.	BC4	0.836	1.348	0.696	Behavioral Component (BC)	Suh and Ahn (2022)
I plan to maintain continuous and frequent use of ChatGPT as a virtual expert to guide me in my academic activities.	BC5	0.838	1.365			
I intend to incorporate frequent use of ChatGPT into my academic routine to obtain answers and support on a consistent basis.	BC6	0.836	1.393			
I will corroborate information obtained through ChatGPT by seeking additional sources before considering it as completely accurate.	BC7	0.856	1.337			
I will validate the information provided by ChatGPT by comparison with academic sources and experts in the relevant field.	BC8	0.844	1.331			
It is not necessary to check the veracity of the information provided by ChatGPT because it always provides valid and reliable information.	BC9	0.793	1.324			
Using ChatGPT in my academic activities develops my autonomous and self-directed learning skills.	CC9	0.873	1.375	0.721	Cognitive Component (CC)	(Schepman & Rodway, 2020; Singh et al., 2020)
Using ChatGPT in my academic activities allows me to explore different perspectives and approaches to address the contents of my subjects.	CC10	0.904	1.366			
Frequent use of ChatGPT, diminishes my abilities to think critically and solve problems independently.	CC11	0.91	1.384			
I am aware that not all answers provided by ChatGPT are correct.	CC12	0.867	1.238			
Frequent use of ChatGPT poses a threat to the privacy and security of my personal data.	CC13	0.849	1.373			
Irresponsible use of ChatGPT can diminish the development of my professional skills.	CC14	0.782	1.371			
I am concerned that frequent use of ChatGPT may limit my ability to think and solve problems independently.	AC11	0.907	1.33	0.763	Affective Component (AC)	Schepman and Rodway (2020)
I am concerned that excessive use of ChatGPT will diminish my interest in researching and reading diverse sources of information.	AC12	0.898	1.385			
When using ChatGPT I carefully check my answers to ensure that they are correct, complete, and free of bias.	BC10	0.871	1.365	0.696	Behavioral Component (BC)	(Conrad & Munro, 2008)
I use ChatGPT responsibly by not presenting technology-generated responses as if they were my own work product, without proper attribution.	BC11	0.85	1.347			
I use ChatGPT responsibly and ethically, ensuring that the answers obtained are a tool to support my learning and not a replacement for my own intellectual effort.	BC12	0.86	1.329			
I use ChatGPT responsibly and ethically, avoiding the generation of misleading, false and/or biased content.	BC13	0.861	1.357			
I strive to understand the limitations of ChatGPT and its potential to generate incorrect or biased responses, which motivates me to use it with caution and discernment.	BC14	0.862	1.356			

Acosta-Enriquez et al. (2024) was made. This instrument analyzes the constructs underlying students' attitudes and determines their intentions to use, verifies information, and responsibly uses ChatGPT.

For its application to participants, Google Forms were used to create an online form with the data collection instrument, which was divided into three sections. The first section included informed consent where all study details were provided, and the anonymity of the participants was assured when completing the survey; at the end of the informed consent, a branching question was asked if they agreed to participate voluntarily in the study. If they indicated "yes," they proceeded to complete the survey; otherwise, "no" automatically closed the survey. The second section included sociodemographic questions such as questions about age, gender, type of university, and the academic program being pursued. In the third section, 40 items were organized, with 14 items belonging to the cognitive component (CC), 12 items belonging to the affective component (AC), and 14 items belonging to the behavioral component (BC). All the items were rated on a 5-point Likert scale ranging from (1) "strongly disagree" to (5) "strongly agree".

4.3. Procedure and data analysis

The survey was conducted in the months of October, November, and December 2023 and in January, February, and March 2024. Prior to its deployment, permission was requested from universities and higher education institutions (HEIs) for the administration of the online survey. After obtaining the necessary approvals, the survey link was distributed via email, where the purpose of the study was explained, and recipients were invited to participate by responding. Additionally, coordination with faculty members was undertaken to share the link through the WhatsApp messaging application, where the purpose of the study was also communicated, and recipients were invited to complete the survey. All participants provided informed consent.

To ensure baseline consistency among the six participating public and private universities, a standardized data collection protocol was implemented. This protocol included uniform training for survey administrators, identical instructions for participants, and a synchronized data collection period across all institutions.

For data analysis, the first step involved cleaning and preprocessing the data via Microsoft Excel, during which missing values and incomplete surveys were identified and removed. Second, descriptive statistics were applied to create Table 1, which presents the sociodemographic results of the participant population. Third, a confirmatory factor analysis (CFA) was conducted to assess convergent validity through indicators such as factor loadings and average variance extracted (AVE), which exceeded the thresholds of 0.70 and 0.50, respectively (Table 2). Internal consistency reliability was also evaluated via Cronbach's alpha and composite reliability (CR) measures (ρ_a and ρ_c), with values surpassing the 0.70 threshold. Discriminant validity was assessed via the Fornell & Larcker criterion and the heterotrait-monotrait ratio (HTMT) criterion, with the results deemed acceptable (Table 3).

Finally, structural equation modeling via the partial least squares (PLS-SEM) technique was performed with the statistical software SMART-PLS v.4.0 version 8.0 (Ringle et al., 2022) to test the proposed research hypotheses.

5. Results

5.1. Results of the measurement model

The partial least squares structural equation modeling (PLS-SEM) method was applied to assess the research hypotheses. As a result, items CC15 and AC13 were eliminated from the confirmatory factor analysis (CFA) to evaluate the convergent validity of the measurement model, as their factor loadings were significantly less than 0.40. After the modification, the measurement model was reprocessed, and as shown in Table 2, the factor loadings of the items were above 0.70, meeting Hair's (2009) criterion. Additionally, all measured constructs present average variance extracted (AVE) values exceeding the threshold of 0.50 proposed by Hair et al. (2017). On the other hand, the standard deviation of the items is between 1.238 and 1.457, indicating that it seems that the items are not excessively dispersed with respect to their means.

Table 3 displays the findings from the tests of discriminant validity and reliability. The metrics Cronbach's alpha (α) and composite reliability (CR) (ρ_a and ρ_c) were employed to evaluate the reliability of the constructs. Values above 0.70 are regarded as sufficient according to Hair et al. (2017) and Nunnally and Bernstein (1994) criteria; as Table 2 shows, all the constructs exceeded this level. Additionally, the coefficient of determination (R^2) values indicate that the cognitive component (CC) explains 86.7% of the variation in the affective component (AC). Moreover, CC and AC together explained 87.5% of the variation in BC.

The discriminant validity was determined in accordance with the Fornell and Larcker, (1981), which requires that the square root of the average variance extracted (AVE) (numbers on the diagonal) exceed the correlations with other constructs (numbers off-diagonal in the same row and column) to establish discriminant validity. The constructs all met this criterion, as illustrated in Table 3. Additionally, the heterotrait-monotrait ratio (HTMT) was employed, where AC had a value of 0.656, BC had a value of 0.537, and CC had a value of 0.637, all of which are below the threshold of 0.85 (Rasoolimanesh, 2022, pp. 1–8), thereby reaffirming that the measurement instrument possesses discriminant validity.

The goodness-of-fit indices of a measurement model constitute a relevant measure for determining convergent validity (Farhi et al., 2023); however, according to Hair (2009), these criteria provide a reference for researchers to determine to what extent the values obtained are well adjusted to the expected values. Table 4 shows the values of the goodness-of-fit indices of the measurement model, where the standardized root mean square residual (SRMR) presented a value of 0.073, satisfying the criteria of (Sun, 2005), where it must be less than 0.85 to be acceptable. The value of Chi-square/gl (χ^2/df) shows that the

Table 4
Model fit.

Criteria	Estimated model	Threshold	Author	Decision
SRMR	0.073	<0.85	Sun (2005)	Acceptable
d_ULS	5.856			
d_G	2.379			
χ^2/df	2.432	Between 1 and 3	Escobedo Portillo et al. (2016)	Acceptable
NFI	0.913	>0.90	Escobedo Portillo et al. (2016)	Acceptable

Table 3
Reliability, discriminant validity, and coefficients of determination.

Construct	α	CR(ρ_a)	CR(ρ_c)	R^2	AC	BC	CC	HTMT
AC	0.844	0.898	0.883	0.867	0.873			0.656
BC	0.964	0.975	0.970	0.875	0.546	0.834		0.537
CC	0.931	0.946	0.939	–	0.499	0.678	0.849	0.637

model has an acceptable fit since it has a value between 1 and 3, as suggested by (Escobedo Portillo et al., 2016). Finally, the value of the normed fit index (NFI) is 0.913, which satisfies the criteria of Escobedo Portillo et al. (2016), where for it to be acceptable, it must exceed the threshold of 0.90.

5.2. Testing the research hypotheses

In Table 5 and Fig. 3, the main results of the analysis conducted via standardized path coefficients (β) are displayed, along with the p values and confidence intervals for β . Path analysis enables the determination of path values between the relationships of exogenous and endogenous variables in the study and the direction of these effects (Hair, 2009; Kelcey et al., 2021). Hypothesis 1 (H1) showed a significant effect between the affective component (AC) and the behavioral component (BC), with a path coefficient of $\beta = 0.672^{***}$ and a p value of $p > 0.000^{***}$, demonstrating that the affective component influences the behavioral component of university students' attitudes toward using ChatGPT. Hypothesis 2 (H2) revealed a significant effect between CC and AC, with a path coefficient $\beta = 0.931^{***}$ and a p value $> 0.000^{***}$, thus proving that the cognitive component influences the affective component of university students' attitudes toward using ChatGPT. Hypothesis 3 (H3) presented a significant effect between CC and BC, with a path coefficient $\beta = 0.260^{***}$ and a p value $> 0.005^{***}$, illustrating how the cognitive component influences the behavioral component of students' attitudes toward using ChatGPTs. Finally, Hypotheses 4, 5, 6, and 7 did not have significant effects and were therefore rejected.

6. Discussion

This study examined the cognitive, affective, and behavioral components of university students' attitudes toward ChatGPT. The research model demonstrated acceptable goodness-of-fit indices, convergent validity, and reliability through confirmatory factor analysis (CFA), with determination coefficients indicating that independent variables adequately account for dependent variables in the SEM.

Hypothesis 1 confirmed that the behavioral component (BC) is positively influenced by the affective component (AC) ($\beta = 0.672^{***}$, $p > 0.000^{***}$). This aligns with prior research identifying intrinsic motivation as a key determinant of ChatGPT usage intention (Lai et al., 2023; Masa'deh et al., 2024). These findings support the link between affective attitudes and behavioral intentions (Ajlouni et al., 2023; Hyeon Jo, 2023).

Hypothesis 2 revealed that the CC positively influences AC ($\beta = 0.931^{***}$, $p > 0.000^{***}$), which is consistent with studies showing that perceived usefulness and informativeness impact attitudes toward ChatGPT (Rahman et al., 2023). This relationship is also observed in STEM fields, where cognitive factors affect affective components (Brown et al., 2017; Rice et al., 2013).

Hypothesis 3 demonstrated CC's positive effect on BC ($\beta = 0.260^{**}$, $p > 0.005^{**}$), supporting previous findings that perceived utility influences behavioral intentions to use ChatGPT (Duong et al., 2023; Masa'deh et al., 2024; Strzelecki, 2023). This aligns with research

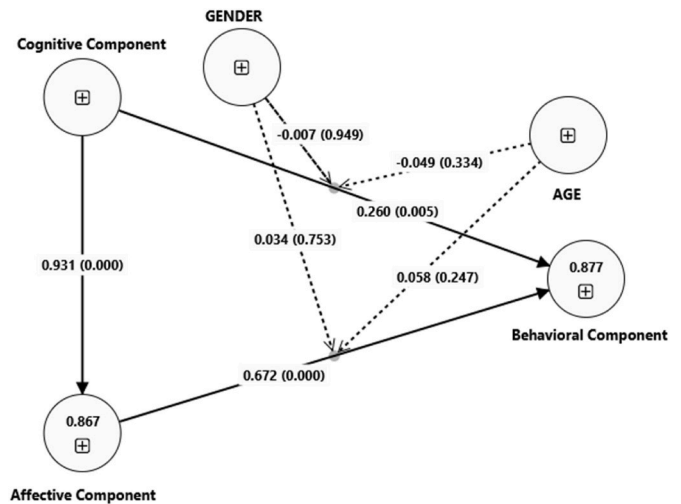


Fig. 3. Resolved research model. Note: At the intersections of the relationship lines are the path coefficients on the left and the p values on the right (inside the parentheses).

showing that cognitive strategies are predictors of academic performance (Peng, 2012).

Hypotheses 4, 5, 6 and 7 revealed no significant moderating effects of gender or age on the relationships between components. While this contrasts with some previous technology adoption studies, it may reflect the unique nature of ChatGPT or the homogeneity of the university student sample. Future research could explore additional demographic variables or employ qualitative methods to uncover nuanced interactions between demographics and attitudes toward AI technologies.

These findings provide new insights into attitudes toward ChatGPT, highlighting the interplay between cognitive, affective, and behavioral components. They also raise questions about the relevance of traditional demographic moderators in this context, suggesting the need to consider other influencing factors.

6.1. Theoretical and practical implications

Theoretically, this study enhances the understanding of generative AI technology adoption in higher education by applying Mitcham's philosophical framework (Mitcham, 1994; Svenningsson et al., 2022). This study confirms the influence of cognitive and affective components on behavioral intentions and establishes a framework for future research on attitudes toward AI in education.

Practically, these findings inform strategies for integrating ChatGPT into educational settings. Educators can design pedagogical approaches emphasizing the benefits of ChatGPT while addressing potential risks. Administrators can develop policies promoting ethical use and academic integrity. Educational technology designers can create interfaces that enhance perceived utility and emotional appeal, optimizing user experiences for meaningful engagement.

Table 5

Path, p value, confidence intervals, standard deviation and decision coefficients.

	Hypothesis	β	p value	2.50%	97.50%	SD	Decision
H ₁	AC→BC	0.672 ^{***}	0.000 ^{***}	0.437	0.829	0.089	Accepted
H ₂	CC→AC	0.931 ^{***}	0.000 ^{***}	0.915	0.951	0.009	Accepted
H ₃	CC→BC	0.260 ^{**}	0.005 ^{**}	0.082	0.441	0.092	Accepted
H ₄	GENDER x CC→BC	-0.007	0.949	-0.238	0.196	0.111	Rejected
H ₅	AGE x AC→BC	0.058	0.247	-0.058	0.165	0.050	Rejected
H ₆	AGE x CC→BC	-0.049	0.334	-0.162	0.067	0.051	Rejected
H ₇	GENDER x AC→BC	0.034	0.753	-0.167	0.259	0.109	Rejected

Note. Path = path coefficient; SE = standard deviation; ^{***} $p < 0.001$; ^{**} $p < 0.01$; ^{*} $p < 0.05$.

6.2. Limitations and future studies

This study, while providing valuable insights, is subject to certain limitations that should be considered when interpreting its results. The primary limitation is the geographical focus on northern Peru, which may limit the generalizability of the findings to other cultural and socioeconomic contexts. Additionally, the use of nonprobabilistic sampling methods introduces potential selection bias, as participants who chose to complete the online survey may not be fully representative of the broader student population.

The cross-sectional nature of the study captures attitudes at a single point in time, precluding the observation of how these attitudes might evolve as students gain more experience with ChatGPT or as the technology itself develops. Furthermore, the reliance on self-reported data may introduce biases such as social desirability or inaccurate self-assessment.

To address these limitations and further advance our understanding of attitudes toward ChatGPT in educational settings, future research could pursue several avenues. Expanding the study to diverse cultural and socioeconomic contexts would increase the generalizability of the findings. Employing probability sampling methods could mitigate selection bias and provide a more representative sample. Longitudinal studies would allow for tracking changes in attitudes over time, offering insights into how perceptions evolve with increased exposure and technological advancements.

Complementing self-report measures with objective methods, such as direct observation of ChatGPT usage or in-depth interviews, could provide a more nuanced and comprehensive understanding of students' attitudes. Exploring additional moderating variables, such as academic discipline or level of technological skill, might uncover important factors influencing attitudes toward ChatGPT. Finally, the use of mixed-method approaches, which combine quantitative surveys with qualitative interviews, could offer a more holistic view of student perceptions and experiences with this emerging technology.

7. Conclusions

This investigation, framed by Mitcham's philosophical framework of attitudes toward technology, provides valuable insights into the psychological mechanisms underlying the adoption of ChatGPT among university students. The study's findings illuminate the complex interplay between the cognitive, affective, and behavioral components of attitudes toward this generative AI technology in the educational sector.

The key results of this research include the significant influence of both affective and cognitive components on the behavioral component of attitudes toward ChatGPT. This underscores the importance of students' emotions, sentiments, beliefs, and perceptions in determining their intention to use this tool. Furthermore, the study revealed a positive effect of the cognitive component on the affective component, suggesting that students' emotional responses to ChatGPT can be shaped by their perceptions of its utility and informativeness.

Interestingly, the study revealed no substantial moderating effects of gender or age on the relationships between attitudinal components. This finding challenges some traditional assumptions about demographic factors in technology adoption and suggests the need for a more nuanced understanding of how individual characteristics interact with attitudes toward AI technologies in educational contexts.

These results substantially contribute to our understanding of the factors influencing ChatGPT adoption among university students. By elucidating the critical role of cognitive and affective components in attitude formation and their impact on behavioral intentions, this study establishes a solid foundation for future research and implementation efforts in educational practice.

The insights gained from this investigation have the potential to inform the development of effective strategies for encouraging the responsible use and adoption of ChatGPT in educational settings. By

addressing the key factors that influence students' attitudes, educators and administrators can work toward smoother and more effective integration of this technology into the teaching–learning process.

Ultimately, this study represents a significant advancement in our comprehension of attitudes toward generative AI technologies in higher education. It opens new avenues for research in this rapidly evolving field, paving the way for further exploration of how these technologies can be best leveraged to enhance educational experiences and outcomes. As AI continues to transform the landscape of higher education, studies such as this will be crucial in guiding the development of policies, practices, and pedagogical approaches that maximize the benefits of these technologies while addressing potential challenges and concerns.

CRediT authorship contribution statement

Benicio Gonzalo Acosta-Enriquez: Investigation, Formal analysis, Data curation, Conceptualization. **Carmen Graciela Arbulú Pérez Vargas:** Writing – review & editing, Conceptualization. **Olger Huamaní Jordan:** Writing – original draft, Investigation. **Marco Agustín Arbulú Ballesteros:** Writing – original draft, Formal analysis, Data curation. **Ana Elizabeth Paredes Morales:** Writing – original draft, Investigation, Conceptualization.

Availability of data and material

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this paper, the author(s) used ChatGPT version 4.0 to improve the writing, language, and readability of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.caeai.2024.100320>.

References

- Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education*, 21(1), Article Scopus. <https://doi.org/10.1186/s41239-024-00444-7>
- Abdaljaleel, M., Barakat, M., Alsanafi, M., Salim, N. A., Abazid, H., Malaeb, D., Mohammed, A. H., Hassan, B. A. R., Wayyes, A. M., Farhan, S. S., Khatib, S. E., Rahal, M., Sahban, A., Abdelaziz, D. H., Mansour, N. O., AlZayer, R., Khalil, R., Fekih-Romdhane, F., Hallit, R., ... Sallam, M. (2024). A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. *Scientific Reports*, 14(1). <https://doi.org/10.1038/s41598-024-52549-8>. Scopus.

- Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Huamaní Jordan, O., López Roca, C., & Saavedra Tirado, K. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information and responsible use. *BMC Psychology*, 12(1). <https://doi.org/10.1186/s40359-024-01764-z>. Scopus.
- Ajlouni, A. O., Wahba, F. A.-A., & Almahaireh, A. S. (2023). Students' attitudes toward using ChatGPT as a learning tool: The case of the university of Jordan. *International Journal of Interactive Mobile Technologies*, 17(18), 99–117. <https://doi.org/10.3991/ijim.v17i18.41753>. Scopus.
- Ajzen, I. (2001). Nature and operation of attitudes. *Annual Review of Psychology*, 52(1), 27–58. <https://doi.org/10.1146/annurev.psych.52.1.27>
- Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. *Computers and Education: Artificial Intelligence*, 6, Article Scopus. <https://doi.org/10.1016/j.caeai.2024.100203>
- Ali, O., Murray, P., Momin, M., & Al-Anzi, F. S. (2023). The knowledge and innovation challenges of ChatGPT: A scoping review. *Technology in Society*, 75. <https://doi.org/10.1016/j.techsoc.2023.102402>. Scopus.
- Aljamaan, F., Malki, K. H., Alhasan, K., Jamal, A., Altamimi, I., Khayat, A., Alhaboob, A., Abdumajeed, N., Alshahrani, F. S., Saad, K., Al-Eyadhy, A., Al-Tawfiq, J. A., & Tamsah, M.-H. (2024). ChatGPT-3.5 system usability scale early assessment among healthcare workers: Horizons of adoption in medical practice. *Heliyon*, 10(7), Article Scopus. <https://doi.org/10.1016/j.heliyon.2024.e28962>
- 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>
- Arrogante, O. (2022). Técnicas de muestreo y cálculo del tamaño muestral: Cómo y cuántos participantes debo seleccionar para mi investigación. *Enfermería Intensiva*, 33(1), 44–47. <https://doi.org/10.1016/j.enfi.2021.03.004>
- Bernabei, M., Colabianchi, S., Falegnami, A., & Costantino, F. (2023). Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances. *Computers and Education: Artificial Intelligence*, 5, Article Scopus. <https://doi.org/10.1016/j.caeai.2023.100172>
- Breckler, S. J. (1984). Empirical validation of affect, behavior, and cognition as distinct components of attitude. *Journal of Personality and Social Psychology*, 47(6), 1191–1205. <https://doi.org/10.1037/0022-3514.47.6.1191>
- Brown, S., White, S., Bowmar, A., & Power, N. (2017). Evaluating an instrument to quantify attitude to the subject of physiology in undergraduate health science students. *Journal of University Teaching and Learning Practice*, 14(1). <https://eric.ed.gov/?id=EJ1142368>.
- Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, 201, Article 123247. <https://doi.org/10.1016/j.techfore.2024.123247>
- Chang, C.-C., & Hwang, G.-J. (2024). ChatGPT-facilitated professional development: Evidence from professional trainers' learning achievements, self-worth, and self-confidence. *s. f. Interactive Learning Environments*, 0(0), 1–18. <https://doi.org/10.1080/10494820.2024.2362798>
- Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, Article Scopus. <https://doi.org/10.1016/j.caeai.2023.100197>
- Choi, E. P. H., Lee, J. J., Ho, M.-H., Kwok, J. Y. Y., & Lok, K. Y. W. (2023). Chatting or cheating? The impacts of ChatGPT and other artificial intelligence language models on nurse education. *Nurse Education Today*, 125, Article 105796. <https://doi.org/10.1016/j.nedt.2023.105796>
- Conrad, A. M., & Munro, D. (2008). *Computer technology use scale*. PsycTESTS Dataset. https://www.academia.edu/26822306/Computer_Technology_Use_Scale.
- Duong, C. D., Vu, T. N., & Ngo, T. V. N. (2023). Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator. *International Journal of Management in Education*, 21(3), Article 100883. <https://doi.org/10.1016/j.ijme.2023.100883>
- Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes* (p. xxii). Harcourt Brace Jovanovich College Publishers, 794.
- Escobedo Portillo, M. T., Hernández Gómez, J. A., Estebané Ortega, V., & Martínez Moreno, G. (2016). Modelos de ecuaciones estructurales: Características, fases, construcción, aplicación y resultados. *Ciencia & trabajo*, 18(55), 16–22. <https://doi.org/10.4067/S0718-24492016000100004>
- Farhi, F., Jeljel, R., Aburezeq, I., Dweikat, F. F., Al-shami, S. A., & Slamene, R. (2023). Analyzing the students' views, concerns, and perceived ethics about chat GPT usage. *Computers and Education: Artificial Intelligence*, 5, Article 100180. <https://doi.org/10.1016/j.caeai.2023.100180>
- Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. <http://people.umass.edu/ajzen/f&a1975.html>.
- Fleckenstein, J., Meyer, J., Jansen, T., Keller, S. D., Köller, O., & Möller, J. (2024). Do teachers spot AI? Evaluating the detectability of AI-generated texts among student essays. *Computers and Education: Artificial Intelligence*, 6, Article Scopus. <https://doi.org/10.1016/j.caeai.2024.100209>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Gao, Z., Cheah, J.-H., Lim, X.-J., & Luo, X. (2024). Enhancing academic performance of business students using generative AI: An interactive-constructive-active-passive (ICAP) self-determination perspective. *International Journal of Management in Education*, 22(2). <https://doi.org/10.1016/j.ijme.2024.100958>. Scopus.
- Graf, A., & Bernardi, R. E. (2023). ChatGPT in research: Balancing ethics, transparency and advancement. *Neuroscience*, 515, 71–73. <https://doi.org/10.1016/j.neuroscience.2023.02.008>
- Hair, J. (2009). *Multivariate data analysis*.
- Hair, J., Sarstedt, M., Ringle, C., & Gudergan, S. (2017). *Advanced issues in partial least squares structural equation modeling*.
- Hu, K. (2023). *ChatGPT sets record for fastest-growing user base—analyst note*. Reuters. <https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/>.
- Jo, H. (2023). Decoding the ChatGPT mystery: A comprehensive exploration of factors driving AI language model adoption. *Information Development*. <https://doi.org/10.1177/026666669231202764>
- Kanabar, V. (2023). An empirical study of student perceptions when using ChatGPT in academic assignments. In T. En Zlateva, & G. Tuparov (Eds.), *Lect. Notes Inst. Comput. Sci. Soc. Informatics Telecommun. Eng.*, 514 LNICST pp. 385–398). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-3-031-44668-9_30. Scopus.
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdell, C., Pfeiffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, Article 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Kelcey, B., Cox, K., & Dong, N. (2021). Croon's bias-corrected factor score path analysis for small- to moderate-sample multilevel structural equation models. *Organizational Research Methods*, 24(1), 55–77. <https://doi.org/10.1177/1094428119879758>. Scopus.
- Kesici, Ş., Sahin, I., & Akturk, A. O. (2009). Analysis of cognitive learning strategies and computer attitudes, according to college students' gender and locus of control. *Computers in Human Behavior*, 25, 529–534. <https://doi.org/10.1016/j.chb.2008.11.004>
- Kong, Z. Y., Adi, V. S. K., Segovia-Hernández, J. G., & Sunarso, J. (2023). Complementary role of large language models in educating undergraduate design of distillation column: Methodology development. *Digital Chemical Engineering*, 9. <https://doi.org/10.1016/j.dche.2023.100126>. Scopus.
- Lai, C. Y., Cheung, K. Y., & Chan, C. S. (2023). Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model. *Computers and Education: Artificial Intelligence*, 5, Article Scopus. <https://doi.org/10.1016/j.caeai.2023.100178>
- Lai, C.-L., & Tu, Y.-F. (2024). Roles, strategies, and research issues of generative AI in the mobile learning era. *International Journal of Mobile Learning and Organization*, 18(4), 516–537. <https://doi.org/10.1504/IJMLLO.2024.141836>
- Lavine, H., Thomsen, C. J., Zanna, M. P., & Borgida, E. (1998). On the primacy of affect in the determination of attitudes and behavior: The moderating role of affective-cognitive ambivalence. *Journal of Experimental Social Psychology*, 34(4), 398–421. <https://doi.org/10.1006/jesp.1998.1357>
- Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploekel, F., Lekkas, D., & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators' perspectives. *Computers and Education: Artificial Intelligence*, 6. <https://doi.org/10.1016/j.caeai.2024.100221>. Scopus.
- Lian, Y., Tang, H., Xiang, M., & Dong, X. (2024). Public attitudes and sentiments toward ChatGPT in China: A text mining analysis based on social media. *Technology in Society*, 76, Article 102442. <https://doi.org/10.1016/j.techsoc.2023.102442>
- Liebrezn, M., Schleifer, R., Buadze, A., Bhugra, D., & Smith, A. (2023). Generating scholarly content with ChatGPT: Ethical challenges for medical publishing. *The Lancet Digital Health*, 5(3), e105–e106. [https://doi.org/10.1016/S2589-7500\(23\)00019-5](https://doi.org/10.1016/S2589-7500(23)00019-5)
- Mahapatra, S. (2024). Impact of ChatGPT on esl students' academic writing skills: A mixed methods intervention study. *Smart Learning Environments*, 11(1), Article Scopus. <https://doi.org/10.1186/s40561-024-00295-9>
- Masa'deh, R., Majali, S. A. L., Alkhaffaf, M., Thurasamy, R., Almajali, D., Altarawneh, K., Al-Sherideh, A., & Altarawni, I. (2024). Antecedents of adoption and usage of ChatGPT among Jordanian university students: Empirical study. *International Journal of Data and Network Science*, 8(2), 1099–1110. <https://doi.org/10.5267/j.ijdns.2023.11.024>. Scopus.
- Mitcham, C. (1994). *Thinking through technology*. University of Chicago Press.
- Noor-Azniza, I., Malek, T. J., Ibrahim, Y. S., & Farid, T. M. (2011). Moderating effect of gender and age on the relationship between emotional intelligence with social and academic adjustment among first year university students. *International Journal of Psychological Studies*, 3(1). <https://doi.org/10.5539/ijps.v3n1p78>. Article 1.
- Nunnally, J., & Bernstein, D. I. H. (1994). *Psychometric theory*. Incorporated: McGraw-Hill Companies.
- OpenAI. (2023). What is ChatGPT? | OpenAI help center. <https://help.openai.com/en/articles/6783457-what-is-chatgpt>.
- Patel, S. B., & Lam, K. (2023). ChatGPT: The future of discharge summaries? *The Lancet Digital Health*, 5(3), e107–e108. [https://doi.org/10.1016/S2589-7500\(23\)00021-3](https://doi.org/10.1016/S2589-7500(23)00021-3). Scopus.
- Peng, C. (2012). Self-regulated learning behavior of college students of science and their academic achievement. *Physics Procedia*, 33, 1446–1450. <https://doi.org/10.1016/j.phpro.2012.05.236>
- Perez-Castro, A., Martínez-Torres, M. R., & Toral, S. L. (2023). Efficiency of automatic text generators for online review content generation. *Technological Forecasting and Social Change*, 189. <https://doi.org/10.1016/j.techfore.2023.122380>. Scopus.

- Pope-Davis, D., & Twing, J. S. (1991). The effects of age, gender, and experience on measures of attitude regarding computers. *Computers in Human Behavior*, 7, 333–339. [https://doi.org/10.1016/0747-5632\(91\)90020-2](https://doi.org/10.1016/0747-5632(91)90020-2)
- Qureshi, R., Shaughnessy, D., Gill, K. A. R., Robinson, K. A., Li, T., & Agai, E. (2023). Are ChatGPT and large language models “the answer” to bringing us closer to systematic review automation? *Systematic Reviews*, 12(1). <https://doi.org/10.1186/s13643-023-02243-z>. Scopus.
- Rahman, M. S., Sabbir, M. M., Zhang, J., Moral, I. H., & Hossain, G. M. S. (2023). Examining students' intention to use ChatGPT: Does trust matter? *Australasian Journal of Educational Technology*, 39(6), 51–71. <https://doi.org/10.14742/ajet.8956>. Scopus.
- Rasoolimanesh, S. M. (2022). *Discriminant validity assessment in PLS-SEM: A comprehensive composite-based approach*.
- Rice, L., Barth, J. M., Guadagno, R. E., Smith, G. P. A., McCallum, D. M., & ASERT. (2013). The role of social support in students' perceived abilities and attitudes toward math and science. *Journal of Youth and Adolescence*, 42(7), 1028–1040. <https://doi.org/10.1007/s10964-012-9801-8>
- Ringle, C. M., Wende, S., & Becker, J. (2022). SmartPLS 4. <https://www.smartpls.com/documentation/getting-started/cite>.
- Rubin, M., Scevak, J., Southgate, E., Macqueen, S., Williams, P., & Douglas, H. (2018). Older women, deeper learning, and greater satisfaction at university: Age and gender predict university students' learning approach and degree satisfaction. *Journal of Diversity in Higher Education*, 11(1), 82–96. <https://doi.org/10.1037/dhe0000042>
- Sallam, M., Salim, N. A., Barakat, M., Al-Mahzoum, K., Al-Tammemi, A. B., Malaeb, D., Hallit, R., & Hallit, S. (2023). Assessing health students' attitudes and usage of ChatGPT in Jordan: Validation study. *JMIR Medical Education*, 9, Article e48254. <https://doi.org/10.2196/48254>
- Sánchez-Reina, J. R., Theophilou, E., Hernández-Leo, D., & Ognibene, D. (2024). Exploring undergraduates' attitudes toward ChatGPT: Is AI resistance constraining the acceptance of chatbot technology? 2076 CCIS. *Scopus*, 383–397. https://doi.org/10.1007/978-3-031-67351-1_26
- Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes toward artificial intelligence scale. *Computers in Human Behavior Reports*, 1, Article 100014. <https://doi.org/10.1016/j.chbr.2020.100014>
- Schönberger, M. (2023). *ChatGPT in higher education: The good, the bad, and the*. University. <https://doi.org/10.4995/HEAD23.2023.16174>. Scopus.
- Šedlbauer, J., Činčera, J., Slavík, M., & Hartlová, A. (2024). Students' reflections on their experience with ChatGPT. *Journal of Computer Assisted Learning*, 40(4), 1526–1534. <https://doi.org/10.1111/jcal.12967>. Scopus.
- Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management*, 50, 191–205. <https://doi.org/10.1016/j.ijinfomgt.2019.05.022>
- Sleiman, K. A. A., Jin, W., Juanli, L., Lei, H. Z., Cheng, J., Ouyang, Y., & Rong, W. (2022). The factors of continuance intention to use mobile payments in Sudan. *Sage Open*, 12(3). <https://doi.org/10.1177/21582440221114333>. Scopus.
- Squalli Houssaini, M., Aboutajeddine, A., Toughrai, I., & Ibrahim, A. (2024). Development of a design course for medical curriculum: Using design thinking as an instructional design method empowered by constructive alignment and generative AI. *Thinking Skills and Creativity*, 52. <https://doi.org/10.1016/j.tsc.2024.101491>. Scopus.
- Strzelecki, A. (2023). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*. <https://doi.org/10.1007/s10755-023-09686-1>. Scopus.
- Strzelecki, A., & ElArabawy, S. (2024). Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology*. <https://doi.org/10.1111/bjet.13425>. Scopus.
- Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *Sage Open*, 12(2), Article 21582440221100463. <https://doi.org/10.1177/21582440221100463>
- Sun, J. (2005). Assessing goodness of fit in confirmatory factor analysis. *Measurement and Evaluation in Counseling and Development*, 37(4), 240–256. <https://doi.org/10.1080/07481756.2005.11909764>. Scopus.
- Svenningsson, J. (2020). The Mitcham Score: Quantifying students' descriptions of technology. *International Journal of Technology and Design Education*, 30(5), 995–1014. <https://doi.org/10.1007/s10798-019-09530-8>
- Svenningsson, J., Höst, G., Hultén, M., & Hallström, J. (2022). Students' attitudes toward technology: Exploring the relationship among affective, cognitive and behavioral components of the attitude construct. *International Journal of Technology and Design Education*, 32(3), 1531–1551. <https://doi.org/10.1007/s10798-021-09657-7>
- Svenningsson, J., Hultén, M., & Hallström, J. (2018). Understanding attitude measurement: Exploring meaning and use of the PATT short questionnaire. *International Journal of Technology and Design Education*, 28(1), 67–83. <https://doi.org/10.1007/s10798-016-9392-x>
- Thorp, H. H. (2023). ChatGPT is fun, but not an author. *Science*, 379(6630). <https://doi.org/10.1126/science.adg7879>, 313–313.
- Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, 10.
- Tu, Y.-F. (2024). Roles and functionalities of ChatGPT for students with different growth mindsets: Findings of drawing analysis. *Educational Technology & Society*, 27(1), 198–214. [https://doi.org/10.30191/ETS.202401_27\(1\).TP01](https://doi.org/10.30191/ETS.202401_27(1).TP01)
- Tu, Y.-F., & Hwang, G.-J. (2023). University students' conceptions of ChatGPT-supported learning: A drawing and epistemic network analysis. *Interactive Learning Environments*, 0(0), 1–25. <https://doi.org/10.1080/10494820.2023.2286370>
- Urban, M., Dèchtèrenko, F., Lukavský, J., Hrabalová, V., Svacha, F., Brom, C., & Urban, K. (2024). ChatGPT improves creative problem-solving performance in university students: An experimental study. *Computers and Education*, 215. <https://doi.org/10.1016/j.compedu.2024.105031>. Scopus.
- Zhang, Y., Yang, X., & Tong, W. (2024). University students' attitudes toward ChatGPT profiles and their relation to ChatGPT intentions. *International Journal of Human-Computer Interaction*. <https://doi.org/10.1080/10447318.2024.2331882>. Scopus.