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Incident factors in the use of ChatGPT and dishonest practices as a system of academic plagiarism: the creation of a PLS-SEM model

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Abstract

The objective of this study was to construct a causal model that explores the factors influencing university students' behavioral intention to use ChatGPT as a learning resource, and to understand the reasons behind their engagement in dishonest practices when incorporating ChatGPT into their academic work. We gathered data through a survey, with the participation of 368 university students. Our analysis employed a causal model based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. On one hand, we verified the hypotheses regarding factors contributing to the intention to use ChatGPT, such as the quality of information generated by the software, the credibility of this information, and student satisfaction with the responses provided. On the other hand, we found compelling evidence of significant factors affecting the intention to use ChatGPT inappropriately, including the absence of clear regulations on plagiarism and corresponding penalties in universities, the students' insufficient research and academic skills (such as conducting research or writing in a scholarly manner), the adverse impact of teachers' workload (excessive tasks or insufficient commitment to assessments), and the general lack of interest and motivation towards academic tasks. Collectively, these factors accounted for 53.20% of the variance in students' behavioral intention to utilize ChatGPT. These findings affirm the effectiveness of this model in explaining the software's role in text production and quality, as well as students' tendencies toward dishonest use.

Keywords: ChatGPT, Didactic resource, Dishonest practices, Plagiarism, Students

Introduction

The field of artificial intelligence (AI) has experienced notable growth in recent years, although it has been the subject of study for several decades. Its origins date back to the late 20th century, when researchers sought to define AI as the ability of machines, robots, computers, or systems to perform tasks in a human-like manner (Simmons & Chappell, 1988). More precisely, Whitby (2009) defined it as the study of behavioral intelligence in humans, animals, and machines and the effort to design and translate this behavior into an artifact, such as computers and computer-related technologies. And with a more current theoretical approach, Lim et al. (2023) defined this as a technology that "(i) leverages deep learning models to (ii) generate human-like content (e.g., images, words) in response to (iii) complex and varied prompts (e.g., languages, instructions, questions)" (p. 2). From these definitions, it is evident that AI has the ability to perform close or human-like functions. However, with the rise of Big Data and advances in computing, AI has been gaining ground and popularity in all sectors of the population (Haenlein & Kaplan, 2019), including education (Alenezi et al., 2023), since this will allow the creation of new content (images, text, music, and videos), learning patterns and structures from existing data (Foster, 2019).

Consequently, educational institutions are increasingly harnessing the power of AI for purposes such as student learning management, intelligent tutoring systems, automated grading, and the implementation of educational chatbots (Crompton & Burke, 2023). From the student's perspective, AI offers the advantage of delivering tailored recommendations for learning resources and activities, providing answers to their queries, and engaging them with pertinent questions to sustain their focus and engagement (Zhu et al., 2023). For educators, the integration of AI into routine and repetitive administrative tasks serves to liberate their time and attention, enabling them to concentrate more on the vital aspects of teaching and student support (Trust et al., 2023). This, in turn, allows educators to allocate additional time to meaningful interactions with their students (Çelik et al., 2022).
Nonetheless, despite its indisputable advantages, the swift evolution of AI has triggered a revolution within the educational system (Javaid et al., 2023), leaving little room for a contemplative assessment of its impact on the educational process. This is evident in the case of the ChatGPT tool, where concerns about plagiarism or students failing to truly grasp the material led several institutions to prohibit its use (Rooney, 2023), or return to evaluation methods reliant on handwritten submissions (Cassidy, 2023). However, some educators are advocating for its incorporation in a reflective, consistent, and appropriate manner (Ausat et al., 2023). This approach might involve prioritizing the cultivation of pertinent questions, fostering discussion, group collaboration, and the development of communication and presentation skills, aspects that fall beyond the purview of ChatGPT (Gardner & Giordano, 2023).

The integration of digital applications in education requires an enhancement of both teachers' and students' digital competency (Oguguo et al., 2023; Guillén-Gámez, Gómez-García et al., 2024), a revision of curricula and instructional approaches (Topsakal & Topsakal, 2022), and a reevaluation of what should be assessed and how to evaluate the final output (Alkhaqani, 2023). Given the increasing utilization of this resource by students, it is imperative for researchers to concentrate on developing models for the technological acceptance of ChatGPT by students, within a techno-pedagogical framework. Dahlkemper et al. (2023) propose an examination of the quality of the information generated by ChatGPT since its accuracy directly impacts student satisfaction (Li & Zhang, 2023). Specifically, the accuracy of ChatGPT depends on the quality and verification of sources, which can lead to inaccurate or unreliable information (Suárez et al. 2024), posing a challenge for people who lack experience in distinguishing between information accurate and misleading. Although some studies in specific areas have reported that ChatGPT demonstrated a satisfactory level of accuracy with results greater than 85% (Samaan et al. 2023), other studies have shown intermediate levels of accuracy with 57.33% (Suárez et al. 2024), depending on the difficulty of the questions, with lower precision for easier questions. To mitigate these risks, Athaluri et al. (2023) and Bhattacharyya et al. (2023) recommends that it is crucial to verify sources, maintain human control, educate users about its limitations, and above all, the impact on response logarithms in ChatGPT from human comments, which would improve accuracy and software consistency (Ouyang et al., 2022). Moreover, educational stakeholders are concerned about the reliability and precision of such information (Trust et al., 2023), as there are instances where it might provide incorrect or incomplete data, potentially leading to misunderstandings or confusion for both students and educators (Sok & Heng, 2023). This project takes into account all these aspects, which will be elaborated upon in greater detail below.

The conceptual framework underpinning the construction of the causal model for ChatGPT's development

There is currently a scarcity of studies delving into the conceptualization of causal models concerning students' behavioral intent to utilize ChatGPT as an educational resource and the factors impacting its adoption. For instance, researchers such as Foroughi et al. (2024) and Strzelecki (2023) explored the predictors of ChatGPT adoption and utilization using the Unified Theory of Acceptance and Use of Technology (UTAUT). Nevertheless, they did not scrutinize the existence of other contributing factors to behavioral intention, which constitutes the primary focus of our study. Among these factors examined in our research are the quality of information generated by the system, student satisfaction, and the potential for dishonest practices associated with plagiarism. The initial model, which has been adapted and extended from the causal models developed by Nelson et al. (2005) and Wixom and Todd (2005), concentrates on a set of factors that elucidate the successful adoption of information, based on the relationships established between information quality, information satisfaction, and technology usage. Grounded in these theories, we have devised the following causal model:

- The Quality of Information (QI) factor plays a pivotal role in the utilization of technological resources (Joo & Choi, 2015). It encompasses the appropriateness of the content provided for addressing academic tasks (Chang et al., 2022), with critical components such as full-text quality, accuracy, and relevance. When it comes to full-text quality, it can be defined as “the extent to which the stored information comprehensively represents all pertinent aspects relevant to the user population” (Nelson et al., 2005, p. 204). Shim and Jo (2020) have emphasized its significance concerning “learner satisfaction with the information,” specifically in our context, the information generated by ChatGPT. As for accuracy, it can be comprehended as “the proportion of correct responses generated by ChatGPT out of the total number of questions posed” (Kusunose et al., 2023, p. 1031). In our study, the accuracy of information generated by ChatGPT refers to content that is free from errors, precise, and correct. As demonstrated by Nelson et al. (2005), accuracy holds a significant role as a determinant of the “student satisfaction with information” factor, which is closely associated with the text produced by ChatGPT. Furthermore, the concept of relevance is construed as “the user’s perception of the degree to which the information is up-to-date” (Wixom & Todd, 2005, p. 91). In our model, relevance is understood as the provision of fundamental, pertinent, and current information by ChatGPT. The predictive relationship between relevance and the “student satisfaction with information” factor has also been established, as students may be influenced by the extent to which the content created by the software is relevant, ultimately impacting their personal satisfaction (Shahzad et al., 2021).
- The Credibility (CR) factor is characterized by the extent to which an information source is perceived as credible, competent, and trustworthy by the individuals receiving the information (Bhattacherjee & Sanford, 2006). Consequently, if a person deems the information source (in our case, ChatGPT) as credible, they are more inclined to seek information from that medium. As asserted by Coursaris and Van Osch (2016), “source credibility plays a pivotal role in the transmission of information and subsequent decision-making” (p. 18). Thus, source credibility positively influences both information quality and information satisfaction (Handayani et al., 2020; Wixom & Todd, 2005).
- The Satisfaction with Information (SI) factor pertains to users’ contentment with the system’s output, website, and support services (Petter et al., 2013), specifically in the context of ChatGPT in our case. Bhattacherjee (2001) expanded upon the Expectancy Confirmation Theory (ECT) to elucidate users’ intention to persist in utilizing an information system, positioning individual satisfaction as a pivotal element (Daneji et al., 2019). Scholars like Çelik and Ayaz (2022) have

underscored how heightened user satisfaction positively correlates with increased product usage.

- Behavioral intention (BI) can be described as the signals or cues that an individual possesses concerning the performance of a particular behavior (Elareshi et al., 2022). In our context, this refers to students' continued use of ChatGPT. Some authors (Anders, 2023; Jarrah et al., 2023) have categorized the intention to use ChatGPT as a form of academic dishonesty, given its potential for facilitating plagiarism. Various factors may influence a student's behavioral intention to use it fraudulently (Jereb et al., 2018). Therefore, it is essential to implement effective pedagogical practices to guide its use as an educational tool (Ollé, 2022).
- The factor of dishonest practices (DP) can be comprehended as the underlying reasons why a student engages in cyber plagiarism within their academic work, and it is divided into four inter-factors. Firstly, one of the motives for these actions, as described by authors like Jereb et al. (2018), is the absence of regulation by university institutions regarding the sanctions for plagiarism (RE factor). Secondly, Meo and Talha (2019) have emphasized that one of the driving factors behind plagiarism is the students' deficiency in academic skills related to research, scientific writing, or citation of authors (LRAS factor). Thirdly, Husain et al. (2017) have highlighted the role of teaching factors in influencing plagiarism, with students finding assignments too challenging, the workload overwhelming, or believing that teachers do not review their assignments (TF factor). Finally, personal factors of the individual, as recognized by authors like Muluk et al. (2021), such as a student's lack of interest and motivation for academic tasks, can also contribute to plagiarism (PF factor).

This study is methodologically significant as there are still relatively few causal models employing variance-based structural equations (PLS-SEM) to unravel the behavior of students when using ChatGPT and the potential factors influencing their dishonest use. This marks a substantial advancement not only empirically but also pedagogically, as it can contribute to the development of educational policies on the appropriate use of this digital resource and the prevention of students engaging in fraudulent practices. Figure 1 illustrates the model proposed for this study, with each factor configured as either an endogenous or exogenous variable based on the hypothesized relationships in the model. The exogenous factors include CR and DP, while the endogenous factors encompass QI, SI, BI, RE, RAS, TF, and PF. The factors RE, LRAS, TF, and PF collectively represent the LOC factors of the DP factor, which is elaborated upon in the subsequent section.

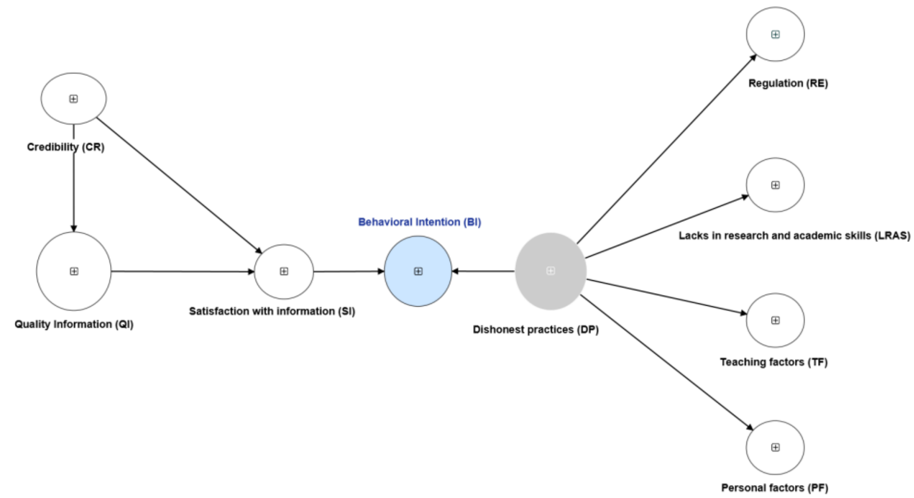

Fig. 1 Design of the causal model. Source: Created by the author

For this study, the following hypotheses were postulated:

- H_1: The Credibility factor significantly predicts the information quality factor generated by ChatGPT.
- H_2: The credibility factor significantly predicts student satisfaction with the information generated by ChatGPT.
- H_3: The higher-order factor named “dishonest practices” significantly predicts students’ behavioral intention to use ChatGPT.
- H_4: The higher-order factor named “dishonest practices” significantly predicts the factor of personal factors for using ChatGPT as a plagiarism system.
- H_5: The higher-order factor named “dishonest practices” significantly predicts the regulation factor.
- H_6: The higher-order factor named “dishonest practices” significantly predicts the factor of “Lack of research and academic skills” for the use of ChatGPT.
- H_7: The higher-order factor named “dishonest practices” significantly predicts the factor of “teaching factors” for the use of ChatGPT.
- H_8: The Information Quality factor has a positive and significant impact on students’ satisfaction with the information generated by ChatGPT.
- H_9: The information satisfaction factor has a positive and significant impact on the continued intention to use the information generated by ChatGPT.

Methodology

- **Design and sample:** The research design employed in this study was ex post facto, characterized by a quantitative and non-experimental explanatory approach. The instrument used for data collection was causal in nature, aiming to elucidate the relationships between factors influencing the intention to use ChatGPT (Cepeda-Carrion et al., 2019). The sampling method chosen was non-probabilistic and purposive. The study encompassed 368 students from the Faculty of Education Sciences at the University of Malaga (Spain), all of whom were enrolled in the course "Communication and Information Technologies Applied to Education" within the Primary Education program. Data collection was facilitated through a survey, and the authors ensured the confidentiality and privacy of the participants' information. This data collection process was conducted in March 2023. Notably, 78.80% (n=290) of the participants identified as female, with an average age of 19.74±3.17 years, while the remaining 21.20% (n=78) identified as male, with an average age of 20.88±6.31 years. At the beginning of the questionnaire three demographic questions were created. The first question was related to the grade obtained to access the university system where students can achieve a maximum score of 14 points. The female gender had an average of 11.02±1.59 points compared to the male gender which obtained an average score of 10.70±1.73. The second question was: Have you used an artificial intelligence application before taking this subject? Regarding the female gender, only 7.90% (n=23) had an affirmative response compared to 92.10% (n=267) who had never used an AI app; while for the male gender, the affirmative response rate was 20.5% (n=16), compared to 79.50% (n=62) who had not used any app with these characteristics. The third question was related to the previous one for those students who had given a positive response in relation to the use of AI applications, where the students had to write the name of the tool previously used. The responses were distributed among the following applications: myAI, Dall-e, and the intelligent systems Siri, Alexa or Google Assistant.
- **Procedure:** The data collection process was divided into two phases. In the first phase, students completed a section of the questionnaire that focused on the potential reasons why they might engage in fraudulent actions, such as plagiarism. In the second phase, as the students had never used ChatGPT before, they were tasked with a specific academic assignment that involved utilizing this software. Upon completing the task, the second part of the questionnaire was administered, focusing on their intention to use ChatGPT based on their experience. The assignment required students to use ChatGPT to request a 500-word text on a topic

related to their subject, such as “Educational innovation vs. technological innovation” or “Emerging technologies applied to digital innovation projects: advantages and dangers.” Using the text generated by ChatGPT as a starting point, students were instructed to verify its accuracy, make any necessary revisions, contribute their own perspectives and opinions, and eliminate any content that was unnecessary or incorrect. To accomplish this, students were expected to search for information in databases such as Scopus and WoS, utilize personal bibliographic management tools like Zotero or Mendeley, and incorporate at least 10 different sources of information (references) to support their work. The final version of the text, along with the initial text generated by ChatGPT, was to be submitted for evaluation by their teachers.

- **Estimation techniques and software.** The creation of the instrument was accomplished using a model based on partial least squares structural equations (PLS-SEM). This technique was implemented with Smart-PLS software, version 4. For the survey, a 7-point Likert scale was employed, with a rating of 1 corresponding to “totally disagree” and a rating of 7 representing “totally agree.” The causal model was constructed using a reflexive-reflexive model and the hierarchical component technique, specifically the repeated indicator approach (Becker et al., 2012). In the causal model (Figure 1), there is a higher-order factor (HCO) referred to as “Dishonest practices,” which is further divided into four lower-order factors (LOC) titled “Regulation, research and academic skills, teaching factors, and personal factors.” The remaining factors within the instrument are categorized as LOC. The procedure for data analysis was as follows. For the lower order factors, it is necessary to check convergent validity, discriminant validity, reliability, and evaluation of the model structure: load, Cronbach’s alpha, average variance extracted (AVE), composite reliability, Fornell-Larcker criteria, Heterotrait-Monotrait Ratio of Correlations (HTMT), and Predictive power (Q2). For the validation of the higher-order factors it is necessary to check the convergent validity, collinearity indicators, and the weights in the path relationships: correlations (R2), VIF (variance-inflation-factor) and path. To this end, Guillén-Gámez, Colomo-Magaña et al. (2024) stated that “the measurement criteria were varied according to the path relationships established between the LOC and HCO factor” (p. 7). The higher-order factor must demonstrate discriminant validity in relation to all its lower-order factors. In addition, it should be taken into consideration that the lower-order factors must exhibit discriminant validity with all other factors of the instrument, except its own higher-order factor of which it is a part (Sarstedt et al., 2019).

Results

The instrument's reliability was assessed, following a procedure similar to that employed by Guillén-Gámez, Colomo-Magaña et al. (2024) in their PLS-SEM study. The assessment involved measuring item factor load (Load), factor reliability (α), and composite reliability of each factor (CR). As recommended by Esposito Vinzi et al. (2010), the factor load for each item should exceed .707, and items falling below this threshold were considered for removal. Similarly, Hair et al. (2019) suggested that Cronbach's alpha coefficient for each latent factor should surpass .700, acknowledging the conservative nature of this reliability coefficient. Additionally, Bagozzi and Yi (1988) recommended verifying CR indices, which should ideally exceed 0.700 as well (Hair et al., 2019). Adhering to these criteria, the authors chose to eliminate specific items that did not meet these standards, namely CR-1, BI-4, SI-3, RAS-2, LRAS-4, and RAS-5.

Secondly, convergent validity was assessed using the Average Variance Extracted (AVE). This index quantifies the degree of correlation among the items within the same factor, indicating how closely the items within a given factor are related (Sarstedt et al., 2014). An AVE value exceeding .50 indicates adequate convergent validity (Wong, 2013). Table 1 reveals that each factor exhibits coefficients surpassing this threshold, with values ranging from .651 to .851.

Thirdly, the discriminant validity of the causal instrument was tested. Rasoolimanesh (2022) states that this index tests how a factor is different from the rest of the factors. To evaluate this index, the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) are used (Henseler et al., 2015). It should be taken into consideration, as stated by Hair et al. (2017) and Sarstedt et al. (2019), that discriminant validity should not be tested for a higher-order model (HOC) concerning its lower-order factors (LOC). In our case, the DP factor repeats the items of the lower-order factors (RE, LRAS, TF, and PF). In other words, the discriminant validity between RE, RAS, TF, PF, and their higher-order factor DP will not be analyzed, so they will appear blank (-).

For the Fornell-Larcker criterion to be met, the square root of the AVE index of each factor must be greater than the correlation with the rest of the factors of the instrument (Rasoolimanesh, 2022). Table 2 shows that the square root of the AVE index (coefficients with gray background) are higher values than the correlations between the factors, thus satisfying the Fornell-Larcker criterion (Fornell & Larcker, 1981).

Table 1 Assessment of the lower-order model

Factor-item	Load	α	CR	AVE
Quality of the information (QI)		*.923*	*.925*	*.651*
QI-1 (Includes all the requested information)	.805			
QI-2 (Is sufficiently comprehensive for the educational task I have to complete)	.813			
QI-3 (Provides all the necessary information)	.830			
QI-4 (Is error-free)	.707			
QI-5 (Is accurate)	.833			
QI-6 (Is correct)	.844			
QI-7 (Contains information that is up-to-date enough for my educational task)	.848			
QI-8 (Is relevant and crucial for my work)	.762			
Satisfaction with information (SI)		*.942*	*.942*	*.851*
IF-1 (In general, the text generated by ChatGPT is suitable for my academic assignment)	.923			
SI-2 (In general, the text generated by ChatGPT is of high quality)	.913			
IF-4 (I am satisfied with the text generated by ChatGPT)	.929			
IF-5 (The text provided by ChatGPT has met my expectations)	.924			
Behavioral intention (BI)		*.895*	*.897*	*.826*
BI-1 (If necessary, I will use ChatGPT again)	.887			
BI-2 (I intend to use ChatGPT as a foundational resource, on which I will work (modify and improve) to write the academic assignment)	.914			
BI-3 (I intend to use ChatGPT as a tool to gather information and, subsequently, write the academic assignment)	.925			
Regulation (RE)		*.896*	*.896*	*.828*
RE-1 (I will use it because I am convinced that the teachers will not be able to check if the information is plagiarism or not)	.891			
RE-2 (I will use it because I am not aware of the sanctions it may entail)	.928			
RE-3 (I will use it because I do not know if there is university regulation against plagiarism)	.911			
Lacks in research & academic skills (LRAS)		*.904*	*.904*	*.839*
RAS-1 (I will use it because I consider that I do not have enough skills to find academic information for my homework).	.916			
RAS-3 (I will use it because I consider that I do not have enough skills in reading comprehension).	.924			
RAS-6 (I will use it because I consider that my homework is not good enough)	.907			
Teaching factors (TF)		*.894*	*.898*	*.758*
TF-1 (I will use it because the homework assignments are too difficult)	.894			
TF-2 (I will use it because the teachers give too many assignments in too little time)	.847			
TF-3 (I will use it because I have the impression that the teachers do not read the students' assignments)	.861			
TF-4 (I will use it because I think I will get a better grade than if I do the homework myself)	.881			
Personal factors (PF)		*.940*	*.940*	*.768*
PF-1 (I will use it because I am lazy and I do not want to spend a lot of time on homework)	.891			
PF-2 (I will use it because I am not interested in learning new content, only in passing the subject)	.885			
PF-3 (I will use it because I consider that it is easier to plagiarize than to work)	.891			
PF-4 (I will use it because other classmates use it)	.865			
PF-5 (I will use it because I do not have time to do the homework)	.846			
PF-6 (I will use it because I always leave homework to be handed in at the last minute)	.880			
Orden Superior (HOC-DP)		*.966*	*.967*	*.652*

Source: Authors' calculations

Table 2 Fornell-Larcker Criterion

	BI	CR	DP	PF	QI	RE	LRAS	SI	TF
BI	.909								
CR	.536	1.000							
DP	.376	.139	.807						
PF	.308	.121	-	.877					
QI	.569	.723	.226	.166	.807				
RE	.391	.159	-	.711	.247	.910			
LRAS	.288	.071	-	.763	.186	.738	.916		
SI	.697	.784	.243	.193	.851	.262	.184	.922	
TF	.407	.173	-	.792	.251	.734	.810	.268	.871

Source: Authors' calculations

Table 3 HTMT Ratio

	BI	CR	DP	PF	QI	RE	LRAS	SI	TF
BI									
CR	.563								
DP	.408	.143							
PF	.339	.127	-						
QI	.620	.752	.240	.180					
RE	.440	.169	-	.774	.273				
LRAS	.323	.075	-	.826	.204	.820			
SI	.756	.809	.256	.207	.893	.286	.200		
TF	.461	.185	-	.861	.277	.819	.894	.296	

Source: Authors' calculations

The suggested thresholds for the Heterotrait-Monotrait ratio (HTMT) criterion should be lower than .90 (Franke & Sarstedt, 2019; Henseler et al., 2015). Table 3 indicates that the HTMT criterion has been satisfied for our PLS model.

Structural model evaluation

Authors such as Hair et al. (2021) and Henseler et al. (2009) outline a series of steps for assessing the causal model.

- First, a multicollinearity analysis using the variance inflation factor (VIF) is necessary (Çakıt et al., 2020). According to the recommendations of Hair et al. (2021), the VIF values for each factor should be below 5. However, authors like Kock (2017) are more stringent in their guidelines, suggesting that a VIF greater than 3.3 could indicate pathological collinearity and the potential presence of common method bias in a model (Kock, 2017, p. 8). Table 4 displays the VIF values among the established hypotheses, with all values being less than 3. Therefore, collinearity is not a concern among the factors in the model.

Table 4 Structural model

Hypothesis	Relationship	VIF	β.	SD	t-value	p-value	Supported	f^2
H_1	CR -> QI	1.000	.723	.031	23.029	.000	YES	1.097
H_2	CR -> SI	2.097	.354	.064	5.576	.000	YES	.277
H_3	DP-> BI	1.063	.220	.028	7.817	.000	YES	.097
H_4	DP-> PF	1.000	.927	.012	76.389	.000	YES	6.088
H_5	DP->RE	1.000	.852	.019	44.294	.000	YES	2.650
H_6	DP-> LRAS	1.000	.911	.012	74.544	.000	YES	4.850
H_7	DP-> TF	1.000	.919	.010	88.955	.000	YES	5.403
H_8	QI-> SI	2.097	.595	.066	8.994	.000	YES	.780
H_9	SI-> BI	1.063	.644	.036	17.790	.000	YES	.833

Source: Authors' calculations

- Secondly, the coefficient β is analyzed to assess the strength of the relationships between the established hypotheses. As pointed out by Purwanto and Sudargini (2021), "its significance can be observed through the t-test derived from the bootstrapping process (a resampling method)" (p. 121). Table 4 provides the standardized weights for each hypothesis, standard deviation (SD), t-statistic (t-value), and the corresponding significance value within a 95% confidence interval (p-value).

Hypothesis 1 examines whether the credibility of the information generated by ChatGPT plays a role in the quality of the information produced by this software. The results revealed a significant relationship between both factors ($\beta = 0.723$, p-value = 23.029, $p < .001$), thereby confirming H1. This means that the more reliable the information created by ChatGPT is, the more likely the text created by this application will also be of higher quality. Therefore, it is essential that language generation models like ChatGPT prioritize accuracy and credibility in their results to improve user experience and encourage responsible use of AI technology.

Hypothesis 2 aimed to determine whether the credibility of the information generated by ChatGPT significantly predicted student satisfaction with the information produced by this software. The findings demonstrated that students' perceptions of information credibility significantly influenced their satisfaction with the information ($\beta = .354$, p-value = 5.576, $p < .001$), supporting H2. Trust in the information provided by ChatGPT is essential to guarantee student satisfaction, and consequently, encourage responsible use of technology. Therefore, it is essential that systems like ChatGPT prioritize accuracy and credibility in information generation to improve the student experience and their trust in the system.

Hypothesis 3 posited that students' perceptions of engaging in dishonest practices by plagiarizing information produced by ChatGPT would significantly influence their behavioral intention to use this software as an academic plagiarism system. The PLS-SEM results showed a substantial relationship between these two factors ($\beta = .220$, p-value = 7.817, $p < .001$), thus providing support for H3. This finding suggests that if students are more inclined to cheat, they are likely to use ChatGPT dishonestly as well. This highlights the importance of promoting ethical and responsible use of technology to avoid unethical behavior.

Hypotheses 4, 5, 6, and 7 examine whether student perceptions of engaging in dishonest practices with ChatGPT significantly impact their internal factors. The results demonstrated the significance of these relationships between the HCO factor and its four inter-factors (LOC). These results show that those students who are going to carry out academic plagiarism with ChatGPT is because they feel that they do not have sufficient academic and research skills, as well as the influence of personal factors and the lack of sanctions for these infractions.

Hypothesis 8 investigates the relationship between the quality of the information produced by ChatGPT and student satisfaction with the information generated by this software. The relationship between these two factors was indeed significant, with a t-value of 8.994 ($\beta = .595$, p-value < 0.05), leading to the acceptance of H8. Therefore, a high quality of the information generated by ChatGPT is closely related to student satisfaction. When information is accurate, relevant, and useful, students feel more satisfied with the results obtained.

Lastly, the connection between student satisfaction with the information created by ChatGPT and the intention to use the software was found to be significant ($\beta = .644$, p-value = 17.790, $p < .001$), thereby confirming H9. That is, when students are satisfied with the quality of the information provided by the software, they are more likely to be willing to continue using it in their academic activities. This highlights the need for businesses to continue improving the quality and accuracy of AI models like ChatGPT to ensure a positive experience and encourage greater usage in the future.

- Thirdly, the analysis of the effect size of the established hypotheses was conducted. According to Janadari et al. (2016), "the assessment of the effect size f^2 seeks to evaluate whether exogenous constructs have a substantive impact on endogenous constructs" (p. 191). As suggested by Aburumman et al. (2022), effect sizes of .35, .15, and .02 are considered large, medium, and small for f^2. The results from Table 4 indicate substantial effect sizes in several relationships. A strong effect is observed between the information credibility factor and information quality ($f^2 = 1.097$). Additionally, relationships between information quality and student satisfaction ($f^2 = .780$) and between student satisfaction with ChatGPT and the behavioral intention to use the software ($f^2 = .833$) all exhibit significant effect sizes.

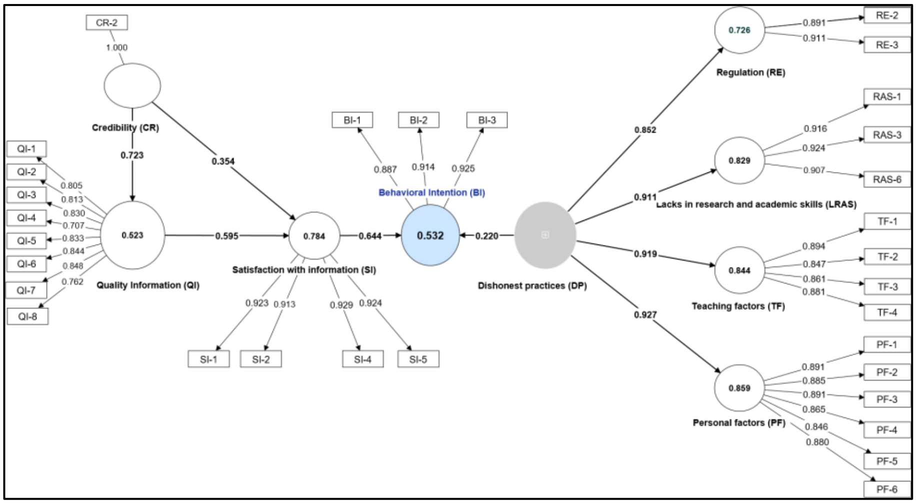

Fig. 2 Smart-PLS – Path Analyses with R-Square Values. Source: Authors' calculations

- Fourth, the coefficient of determination (R^2) for the endogenous constructs (QI, SI, BI, RE, RAS, TF, and PF) was assessed. This index represents the predictive power of the sample, and values range from 0 to 1, with higher values indicating stronger explanatory power (Rigdon, 2012). According to Hair et al. (2019), thresholds close to .25, .50, and .75 are considered to represent weak, moderate, and substantial explanatory power, respectively. As illustrated in Figure 1, the model exhibits good explanatory power with R^2 values of .523 for QI, .784 for SI, .532 for BI, .726 for RE, .829 for RAS, .844 for TF, and .859 for PF.
- Finally, predictive relevance (Q^2) was assessed to determine the predictive validity of the causal model (Stone, 1974). Q^2 values of .02, .15, and .35 are indicative of small, medium, and large predictive power, respectively, for an exogenous factor on an endogenous factor. The blindfolding data revealed the following prediction sizes: BI, Q^2= .368 (large); LRAS, Q^2= .829 (large); PF, Q^2= .859 (large); QI, Q^2= .518 (large); RE, Q^2= .725 (large); SI, Q^2= .614 (large); TF, Q^2= .843 (large). Thus, the model demonstrates a highly satisfactory predictive ability.

Discussion

Advances in artificial intelligence have allowed society to evolve from technologies that can perform functions similar to those of humans, known as intelligence systems (Whitby, 2009), to the possibility of creating new content from information, known as generative AI (Foster, 2019). Education stands as a field of knowledge where the application of generative AI is expanding exponentially, especially driven by the adoption of ChatGPT tools for the creation of textual content.

The primary objective of this study was to scrutinize the construction of causal models concerning the behavioral intention of university students to incorporate ChatGPT as a learning resource, as well as to explore the factors that influence its utilization. To achieve this, we developed an instrument by building upon and extending the causal models put forth by Nelson et al. (2005) and Wixom and Todd (2005). These models delved into the factors that elucidate the effective adoption of information. In our work, we adapted and extended these models to encompass the unique characteristics of ChatGPT, introducing specific factors related to the software's features, while also integrating additional factors gleaned from the practical implementation of this technology.

The instrument, with an initial design of 37 items and 2 exogenous and 7 endogenous factors, was submitted to a psychometric validation process. Those items that did not meet the psychometric requirements were eliminated. The final version consisted of 31 items distributed as follows: credibility factor (1 item); dishonest practices factor, conceived as a higher order factor composed of 4 inter-factors that would make up the lower order: regulation (2 items), gaps in research and academic competencies (3 items), teaching factors (4 items) and personal factors (6 items); information quality factor (8 items); information satisfaction factor (4 items); and behavioral intention factor (3 items). The reliability of the instrument showed very satisfactory coefficients in all factors. The data of the proposed model showed adequate convergent and discriminant validity in the criteria analyzed (Henseler et al., 2015).

Assuming that ChatGPT is an AI chatbot capable of interactive communication with users based on their questions and topics, it becomes evident that the quality of the information generated by the software significantly influences the credibility users assign to it. It is crucial to recognize that AI continuously learns from existing information, which can introduce an element of uncertainty regarding the reliability of the information it generates, as noted by Sok and Heng (2023). Consequently, hypothesis H1, which posits this relationship, has been confirmed with a substantial and lasting effect (f^2= 1.097). This reaffirms the importance of scrutinizing the quality of information produced by this software, a concept supported by Dahlkemper et al. (2023), due to its profound impact on users' trust in it, as observed by Coursaris and Van Osch (2016). A plausible explanation for the level of trust may be the good quality of the information generated by ChatGPT, understanding this as the precision, relevance, and global value of the text (Chang et al., 2022), a credibility which is due to the high success rate of this tool (Choi et al., 2022). Such credibility also depends on the quality and precision of the questions asked, forming prompts with clear guidelines about the information we want. Furthermore, understanding that both the quality and credibility of the information generated by ChatGPT foster recurrent use by university students, it becomes necessary not only to establish guidelines for its incorporation into the educational process but also to consider the need for revising educational policies, teaching methods, and the assessment of knowledge itself, as emphasized by Alkhaqani (2023) and Topsakal and Topsakal (2022).

Furthermore, our collected data have provided statistical evidence supporting hypothesis H2, which pertains to the relationship between credibility (CR) and satisfaction (SI) concerning the information generated by ChatGPT. This relationship has been found to be statistically significant, thus confirming the hypothesis. In essence, the content produced by ChatGPT is considered credible and trustworthy by university students. This factor exerts a moderate effect (f^2= .277) on the level of satisfaction that users experience with the information generated, aligning with the findings of other researchers (Handayani et al., 2020; Wixom & Todd, 2005). This outcome substantiates the assertion made by Li and Zhang (2023), who contend that if the information is credible and of high quality, student satisfaction regarding its use will naturally increase. Consequently, the credibility and quality of information further promote the utilization of ChatGPT, as the high level of accuracy it achieves enhances student confidence and satisfaction with the software (Trust et al., 2023). Therefore, the findings indicate that student satisfaction with ChatGPT information is linked to confidence in the validity of the content produced, taking into account that if the student is satisfied with the information received, they are also more likely to perceive it as credible and trustworthy. In this way, satisfaction can act as a positive cognitive filter, making the person more receptive to accepting information as accurate and truthful. However, as already highlighted by Suárez et al. (2024), ChatGPT can spread disinformation that has not been scientifically verified, so the level of accuracy may be affected. Therefore, before using the information provided by the software, authors such as Athaluri et al. (2023) propose that it is necessary to verify information sources, as well as continue to reinforce software optimization based on human comments (Ouyang et al., 2022). From our perspective, and considering the pros and cons of this digital tool, the use of ChatGPT can serve as a starting point to carry out the academic activities of the students and complement it with the intellectual work of being a student, reviewing the information through repositories with high scientific quality such as WoS and Scopus. In this way, it would be possible to guarantee a higher percentage of the accuracy of the information provided by the software, and at the same time improve the language and patterns of the system itself.

Another facet of our analysis delves into how students' perceptions regarding engaging in dishonest practices when using ChatGPT in their academic work influence the likelihood of such behavior. Our study's data underscore a significant predictive relationship between dishonest practices and the behavioral intention to use this software, thus confirming H3. In essence, an increase in certain behaviors encompassed within the broader category of dishonest practices corresponds to a heightened inclination to utilize this tool. Therefore, the intention to use ChatGPT wields a substantial impact, even if at a smaller β level, on the perception of dishonest practices associated with this resource, a phenomenon that has been observed in previous studies (Anders, 2023; Jarrah et al., 2023; Jereb et al., 2018). An explanation to consider is that these findings are linked to the subfactors that cause dishonest practices, especially those related to the purpose of the tasks and the time it takes to complete them. That is, students prioritize not wasting time on actions that will have little importance in their grades or learning process, using ChatGPT to handle mechanical tasks, allowing them to focus their learning time on more meaningful elements. However, it is indeed intriguing to investigate in future research why, despite the reduced significance, such a connection exists between these factors, especially when fraudulent practices themselves have prompted numerous universities to impose bans on their use (Rooney, 2023). Addressing this issue necessitates the cultivation of moral and ethical awareness among students regarding the responsible use of ChatGPT. Additionally, educators should develop pedagogical approaches that foster skills beyond the mere application of ChatGPT, such as critical thinking and reflective capacities (Ausat et al., 2023; Gardner & Giordano, 2023).

In our proposed model, it has been confirmed that students' dishonest use of ChatGPT is indeed associated with dishonest behaviors on their part. As our results affirm, the escalation of certain interrelated factors (RE, LRAS, TF, PF) contributes to an increase in dishonest practices (DP), and these factors collectively help construct a comprehensive understanding of fraudulent behaviors with ChatGPT. In this context, hypotheses H4-H7 have been substantiated. Consequently, it becomes evident that dishonest practices with ChatGPT are influenced by students' perceptions of specific behaviors and self-conduct, a finding that is consistent with existing studies (Husain et al., 2017; Jereb et al., 2018; Meo & Talha, 2019; Muluk et al., 2021). This discovery underscores the need for designing educational approaches in university settings that target the reduction or elimination of such fraudulent or dishonest tendencies (Opara et al., 2023). It also underscores the importance of developing regulations to address plagiarism involving AI, enhancing students' scientific skills, and making academic tasks more engaging to discourage dishonest behavior. A plausible explanation for these dishonest practices is related to highly competitive educational environments or where the final result is valued more than the learning process, making ChatGPT a facilitating tool for their academic responsibilities. Furthermore, some students may feel excessive pressure to obtain good grades at any cost. This pressure can lead to dishonest behavior, such as incorrect use of ChatGPT, to cope with academic expectations and demands (Ventayen, 2023).

This model also examines the hypothesis that the quality of the information produced by ChatGPT impacts student satisfaction with the content generated by this tool. The relationship between these two factors proved to be significant and displayed a substantial effect (f^2= 0.780), thus confirming H8. Therefore, it is evident that various facets contributing to information quality exert an influence on student satisfaction. In particular, the quality of the generated text itself, as indicated by Çelik and Ayaz (2022), and the accuracy of the text, as pointed out by Kusunose et al. (2023), emerge as noteworthy factors affecting student satisfaction (Nelson et al., 2005). Consequently, if this software consistently produces accurate and high-quality content, it prompts academic institutions to reconsider the nature of the final output they expect from their students as evidence of the acquisition and development of learning competencies (Alkhaqani, 2023). ChatGPT can then serve as an additional resource in the students' formative journey, rather than being utilized as a dishonest solution to their academic responsibilities (Cassidy, 2023). The findings also indicate that aspects such as the relevance and timeliness of the generated content were factors that also condition student satisfaction, as was already the case in the study by Shahzad et al. (2021). Thus, confidence that the information returned by ChatGPT is accurate and current is a fundamental pillar of its proliferation and use in the academic sphere by university students.

In summary, the relationship examined in H9, which connects user satisfaction with the information (SI) to the behavioral intention to use ChatGPT, has been empirically validated. This confirms that a higher level of satisfaction with the information offered by ChatGPT to university students is associated with a stronger intention to utilize the service. This finding aligns with the established theory that user satisfaction with an information system, as observed in this case (Daneji et al., 2019), leads to increased user usage (Çelik & Ayaz, 2022). This trend can be largely attributed to ChatGPT's remarkable capacity to provide personalized responses to questions and suggest tailored activities (as exemplified by Zhu et al., 2023). Consequently, ChatGPT serves as a tool that efficiently delivers content and resources to university students, marked by high quality and speed, thereby encouraging its recurrent use by its users. Given the significant relationship between student satisfaction with the information offered by ChatGPT and the behavioral intention to use this software, it is imperative to establish, within the university academic environment, the criteria and principles that regulate its use as an educational tool to be integrated into the teaching and learning process (as recommended by Ollé, 2022). In addition, this satisfaction is also linked to the time and effort savings that would result from searching for information in multiple sources or performing repetitive tasks, being able to obtain accurate answers quickly and efficiently with ChatGPT (Zhu et al., 2023). Thus, this tool meets various academic needs quickly and with quality, which reinforces the exponential proliferation of its use as long as tasks continue to involve text production and closed-ended responses rather than creation and innovation by students.

Conclusion

The introduction of ChatGPT into the academic sphere, an AI chatbot that engages users based on their questions, presents several key requirements. Firstly, there is a pressing need to enhance the digital literacy of potential users, encompassing both students and educators (Oguguo et al., 2023). Additionally, there is a need to establish techno-pedagogical models for the effective utilization of this tool by students. This latter aspect served as the focal point of our study, contributing significantly to the body of scientific knowledge in this area by constructing a causal model that explores the behavioral intention to employ ChatGPT as a learning resource, alongside the factors that influence its usage. By employing variance-based structural equation modeling (PLS-SEM), we have not only validated the significance of the relationships among the model's constituent factors but also elucidated their effects.

Thus, the perception of quality of the answers was valued satisfactorily by the students. This fact leads to an increase in its use in academic practice, forcing the teacher to make theoretical-practical changes in the training process. In this sense, it is necessary to rethink other types of tasks that demonstrate the acquisition of skills in different subjects (Alkhaqani, 2023), as well as modify teaching techniques and the way of assessing. It is necessary in future work to delve into innovative and creative aspects regarding the production of content, to promote the critical and reflective skills of students to use this tool as a training and teaching resource. Likewise, factors such as the lack of research and academic skills of the students, the difficulty of the tasks and the low quality of the teaching corrections or the disinterest of the students themselves in their learning increased the fraudulent use of this software. In this way, the changes must be carried out at a pedagogical level from the institution, with the purpose of reducing the presence of these factors in the training process, requiring an ethical-moral level on the part of the students about the importance of learning beyond of simply passing a subject. Furthermore, the relationship between satisfaction with information and dishonest practices was significant, which reinforces the need to design educational policies that regulate and stipulate the pedagogical way of using this software, taking into account the potential of the information it generates as a resource for the learning process.

In addition to examining the relationships associated with the behavioral intention to use ChatGPT, it is imperative to reflect on the study's design and methodology. One notable limitation was the non-probabilistic sampling, which calls for caution when extending the findings to samples of university students with similar characteristics. To address this limitation in future research, employing probabilistic sampling methods and enlarging the sample size would enhance the generalizability of the results. Regarding the characteristics of the sample, it is also necessary to consider the gender imbalance, since the predominance of female participants means that the results may not favor those of the male sex.

Furthermore, choosing exclusively students from the knowledge area of Educational Sciences with experience in the subject of educational technology gives it a unique and distinctive component, which must also be considered when extrapolating the findings. Another limitation could be the suitability of ChatGPT as a generative AI for different areas of knowledge. Although it seems excellent for areas such as literature and acceptable for science, it is less efficient for other areas such as social sciences and art. Therefore, it would be interesting to analyze the user behavior or dishonest practices of students in other specific AIs for different areas of knowledge such as art or music.

In summary, the decision of university students to use ChatGPT is influenced by a myriad of interconnected factors. These factors are associated with the software's capacity to generate text and its quality, as well as the students' inclinations towards dishonest use. Therefore, it is essential to acknowledge both dimensions when comprehending the motivations behind the adoption of this tool by university students. This, in turn, paves the way for the implementation of enhancements to ensure that the use of ChatGPT aligns with pedagogical and ethical principles.

Abbreviations

AI: Artificial Intelligence; AVE: Average Variance Extracted; ECT: Expectancy Confirmation Theory; HTMT: Heterotrait-Monotrait Ratio of Correlations; PLS-SEM: Partial Least Squares Structural Equation Modeling; SD: Standard Deviation; UTAUT: Unified Theory of Acceptance and Use of Technology; VIF: Variance-Inflation-Factor.

Authors' contributions

The first author conducted this research, designed the study, carried out the research methods, performed the analysis, developed the framework, and wrote the manuscript with support from the second and third authors. The fourth author contributed to the planning and overall research, as well as editing the manuscript.

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