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Students' perceptions, attitudes and utilisation of ChatGPT for academic dishonesty: Multigroup analyses via PLS–SEM

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Abstract
While previous studies have explored students' use of different AI tools for academic purposes, studies that have specifically investigated students' use of ChatGPT for dishonest academic purposes in Nigeria are lacking. The consequence of this contextual and knowledge gap is a lack of specific understanding regarding students' engagement with ChatGPT for academic dishonesty in Nigerian tertiary institutions. This study addressed these gaps by examining students' perceptions, attitudes, and utilisation of the ChatGPT and determining the role of sex and age in these linkages. A sample of 4679 public university students participated in the study. Structural equation modelling and multigroup analysis were performed to test the conceptual model with the aid of SmartPLS 3. The results indicated that, regardless of sex or age, students with positive perceptions of ChatGPT were more prone to use it for dishonest academic purposes. The study noted a sex disparity in the direct impact of perception on ChatGPT use, which was particularly pronounced for female students. Significant age-related differences were observed, with a stronger effect observed for younger students. A negative direct effect of attitude on ChatGPT use for academic dishonesty was recorded, with attitude further serving as a significant negative mediator of the relationship between perception and ChatGPT use. This mediating effect was consistent across sexes but varied with age, being stronger among younger students than among their older counterparts. This study underscores the need to foster positive attitudes among younger students to counteract the appeal of using the ChatGPT for academic dishonesty.

Keywords Academic integrity · Age · Artificial intelligence · Sex · Unethical practices

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1 Introduction

The advent of artificial intelligence, especially large language models (LLMs), such as the ChatGPT, has attracted much attention among scholars. ChatGPT is among the most important innovations that can support teaching and learning (Demirkol & Malkoc, 2023; Karakose & Tülübaş, 2023; Okonkwo & Ade-Ibijola, 2021), school administration (Chen et al., 2020), classroom assessment (Owan et al., 2023b), student engagement (Maier & Klotz, 2022; Popenici, 2023) and academic achievement (Chen et al., 2020; Owoc et al., 2021). ChatGPT is a conversational agent that utilises natural language processing (NLP) to generate intelligent responses from computers in diverse subject matter (Tlili et al., 2023), as requested by the user. It acts as a human, responding to questions, correcting mistakes made in previous questions, and rejecting requests that are very inconsistent and incoherent (Chen et al., 2020; Zawacki-Richter et al., 2019). Although still evolving, ChatGPT provides a large set of information, human-like text generation, and fine-tuned responses to issues that intelligent people in different professions can also handle (Rudolph et al., 2023).

Given its growing importance, many institutions and stakeholders are gradually contemplating whether AI in general and ChatGPT in particular should be formally integrated into their curricula (Owan et al., 2023b). Some researchers have noted that students utilise ChatGPT to commit high levels of plagiarism, ghost authorship (Ofem et al., 2023), examination malpractice (Baidoo-Anu & Ansah, 2023), and academic laziness (Zhang, 2023), among others. The relevance of the ChatGPT in academia has been questioned (Ondřej & Woithe, 2023). Similarly, ChatGPT has been associated with unethical practices that contradict the constructivist perspective of students' active participation in learning because it creates content that may be biased (Muhajirah, 2020; Zajda, 2021), destroying the spirit of learning and academic integrity. Moreover, ChatGPT use has been associated with academic fraud, malpractice, plagiarism, and privacy erosion (Garg & Goel, 2022; Gašević et al., 2023). Consequently, the misuse of these tools and the inadequacy of current detection methods have led some institutions to ban ChatGPT use for different purposes (Lim et al., 2023).

Despite the various commentaries and opinions on the negative use of the ChatGPT and every other potential disadvantage associated with its use, no previous research has specifically examined the extent to which higher education students use AI tools (particularly the ChatGPT) for academic dishonesty. As a result, it remains unclear whether the claims made about the ChatGPT in promoting academic dishonesty are true and, if so, to what extent. Although two studies have attempted to examine higher education students' perceptions of using ChatGPT for academic dishonesty (Chan & Hu, 2023; Ngo, 2023), nothing from these studies was specific about its utilisation for academic dishonesty. Existing studies have shown that students' perceptions and attitudes are important when using ICT resources (Owan et al., 2023a; Petters et al., 2024). Moreover, students' attitudes are connected to their perceptions of the ChatGPT (Albayati, 2024). Therefore, examining whether using the ChatGPT for academic dishonesty as an antecedent of students' perceptions and attitudes is also important. Along these lines, the present study aimed to: (1) examine how students' perceptions are related to their attitudes and actual use of ChatGPT for academic dishonesty; (2) investigate the relationship between students' attitudes and use of ChatGPT for academic dishonesty; (3) determine the extent to which students' attitudes mediate the relationship between their perceptions of and actual use of ChatGPT for academic dishonesty; and (4) verify whether the direct and mediating effects of the model vary with students' age and sex.

2 Literature review and hypothesis formulation

2.1 Students' perception of ChatGPT

Many studies have examined students' perceptions of ChatGPT in higher education (e.g., Hwang & Tu, 2021; Liang et al., 2021). Previous studies have produced different results on students' perceptions of ChatGPT. This is attributable to ethical issues and concerns regarding ChatGPT use in academic settings (Agyemang et al., 2023; Muhajirah, 2020; Zajda, 2021). Some studies have shown that students positively perceive the use of AI, especially for research writing (Bisdas et al., 2021; Sassis et al., 2021).

The rationale could be that ChatGPT helps students generate study-specific and related content, which deepens their understanding of the object of study (Karakose & Tülübaş, 2023). These findings can be content- and context specific. This is because the perceptions that students in a locale may have toward ChatGPT may be influenced by many factors that may be unique to those settings. For instance, in Nigeria, AI has not been fully integrated into the curriculum, and those currently utilising it may stem from their awareness of ICT (Owan et al., 2023b). Thus, it is unclear whether students perceive this phenomenon positively (Fahmi & Cahyono, 2021; Li, 2023; Miranty & Widiati, 2021).

Chan and Hu (2023) revealed positive student attitudes toward genAI. However, the level of perception is uncertain because it focuses more on privacy, ethical considerations, and its impact on professional development. In contrast, other researchers have noted that students' perceptions of AI are gradually changing, probably due to its relevance, which has been identified by most students for learning, data collection, and interpretation of results, among other reasons (Fahmi & Cahyono, 2021; Miranty & Widiati, 2021). Moreover, Singh et al. (2023) discovered that even though students are familiar with ChatGPT, they negatively perceive its usage for academic purposes. Similarly, other scholars have revealed students' negative perceptions of AI (Ibrahim et al., 2023), particularly ChatGPT. Due to the disagreements among scholars on the nature of students' perceptions, there is an evidence gap (Ekpenyong et al., 2023), suggesting that further studies are needed to clarify these arguments across contextual lines. Consequently, the first two hypotheses were developed:

H_1: Students' perceptions significantly predict their attitudes toward using ChatGPT for academic dishonesty.

H_2: Students' perceptions significantly predict their use of the ChatGPT for academic dishonesty.

2.2 Students' attitudes toward using the ChatGPT

Attitudes are individuals' dispositions toward objects and phenomena (Chen et al., 2023). Studies have shown that students have high positive attitudes toward using ChatGPT (Sallam et al., 2023). The advent of advanced technologies like AI has brought dramatic dynamics in the educational ecosystem that seriously threaten academic integrity (McCabe & Treviño, 1993). Students' attitude to this technology may influence their decision to use it positively or negatively. Therefore, understanding students' attitudes is important to aid educators and policymakers foster ethical behaviour. The attitude of students to the use of ChatGPT may be informed by their perceived benefit of the tools. Suppose students perceive that utilizing these tools can provide quick access to information, assistance in research and any other writing task and explanation to complex issues. In that case, they may exert positive energy on these tools (Venkatesh & Davis, 2000). Therefore, students' attitude to ChatGPT is predicated on either perceived use, ease of use or other internal or external factors that motivate their disposition to it (Davis, 1989; Whitley, 1998). This aligns with the technology acceptance model (TAM) that posits that perceived usefulness and ease of use are essential drivers of user's attitudes to technology. The ethical implication of using ChatGPT cannot be ruled out; most students' attitudes to ChatGPT are propelled by their awareness of issues of privacy, data security, and equity in using these tools. Students who are worried about the ethical implications of these tools may not be interested, and this may inform their negative attitude toward it. However, this doe does not rule out the relevance of these modern tools.

Attitude may also serve as a potent link between how ChatGPT is perceived and what students actually do with it for various academic purposes. For example, when students perceived that ChatGPT can be veritable to influence better research work and academic outcome, their disposition to this tool may also be positive (Venkatesh & Davis, 2000). Conversely, students who are aware of the ethical implication of misusing ChatGPT may also ensure that they develop a negative attitude to use of it. This is supported by a study form Stone et al. (2010) that found that students' attitudes towards cheating mediated the relationship between their beliefs about the ease of cheating and their actual cheating behaviour. Other empirical studies have shown that attitude is a strong predictor of student's use of ChatGPT. Another study revealed a moderate positive attitude among students toward using ChatGPT (Huallpa et al., 2023). Across studies, evidence consistently links greater intellectual humility to positive attitudes toward ChatGPT, with openness mediating the effect (Li, 2023). Another study revealed that the attitudes of early adopters toward the ChatGPT are diverse, with some using it as a transformative tool to enhance their self-efficacy and learning motivation. In contrast, others are apprehensive, worrying about their potential loss of critical thinking skills (Hadi et al., 2024). The study of Smith and Jones (2024) found that students who are under academic pressure have the likelihood to use ChatGPT for academic dishonesty. Johnson et al. (2023) admitted that academic pressure is a significant cause for student's use of ChatGPT for dishonesty. In another survey, Lee and Kim (2023) found that students with higher levels of technological literacy were more aware of the ethical issues related to using ChatGPT for academic dishonesty. However, this awareness did not necessarily deter misuse; rather, technologically literate students often justified their use of ChatGPT as a learning tool rather than a means of cheating. Other studies that corroborated these findings are documented in literature (Martinez & Hall, 2024; McCabe & Treviño, 1993). Previous research has reported disparities in students' attitudes toward using the ChatGPT, suggesting that context might be important in understanding AI use. Consequently, the following hypotheses were framed:

H_3: Students' attitudes significantly predict their use of ChatGPT for academic dishonesty.

H_4. Attitude significantly mediates the relationship between students' perceptions and their actual use of ChatGPT for academic dishonesty.

2.3 Utilisation of the ChatGPT for academic dishonesty

The introduction of the ChatGPT in the educational sector has triggered a paradigm shift in the academic literature search, and its use has been extensively appreciated (Adarkwah & Huang, 2023; Popenici et al., 2023; Xames & Shefa, 2023). Similarly, Tareq et al. (2023) discovered that using AI tools in higher education has allowed students to explore diverse research materials, provide feedback, collect, analyse, and interpret data, and access a wide spectrum of information that hitherto was difficult.

On the other hand, various concerns about using the ChatGPT in education, including tracking academic dishonesty and cheating, have been reported. For instance, Aydın and Karaarslan (2022) used ithentication software to check the similarity level of texts generated by ChatGPT and found that ChatGPT could not produce original texts after paraphrasing. In addition, Mills et al. (2023) reported that this language transformer tool could be the "death knell" of academic publishing because it could create "cheating and academic fraud" on a massive scale, which ultimately impacts scholarly creativity, innovative writing, and intellectual property rights. It, therefore, comes as no surprise that out of 34 expert markers recruited by Cardiff University in the UK, 23% could not distinguish between essays written by undergraduate students and those generated by ChatGPT, while 19% could not do the same for graduate-level papers (Ngo, 2023). Moreover, questions have been raised about whether the ChatGPT could end the reign of academic honesty (Karadağ, 2023). Jarrah et al. (2023) reported that ChatGPT can lead to plagiarism, depending on its use. Moreover, students with access to these tools are also reported to take undue advantage, as most teachers and school administrators cannot detect AI-generated texts convincingly (Hosseini et al., 2023). A few published studies on the ChatGPT from an African perspective and in higher education (e.g., Chaka, 2023; Ifelebuegu et al., 2023). This explains why some researchers recommend investigating ChatGPT regarding awareness and acceptance (Rudolph et al., 2023). Moreover, Singh et al. (2023) discovered that even though students are familiar with ChatGPT, their utilisation of academics is low.

2.4 Sex differences

Demographic analysis of respondents' perceptions and attitudes toward utilising the ChatGPT is important for policy purposes. Studies have shown differences between male and female students concerning the utilisation of ICT for various purposes. For example, several African studies have shown that male students utilise ICT more than female students do (Owan et al., 2023a; Syed & Al-Rawi, 2023). Similarly, Kashive et al. (2020) showed, through a multigroup analysis, that the prediction of attitudes and satisfaction on students' intentions to use e-learning modules varied with sex and learner type. Reports on sex differences in AI are rather confusing (McGregor et al., 2017), suggesting that studies establish sex differences in all forms of relationships discovered for the general population (Owan et al., 2023a).

In contrast, some studies have found no significant difference in ICT use among male and female students. For example, Petters et al. (2024) discovered that although males are not significantly different from females, their use of ICT for data collection differs. Another related study revealed that dishonest practices, such as cheating, plagiarism, and falsification, are common among male and female students, but there are no significant sex differences (Owan et al., 2023c). Apart from the knowledge gaps arising from the scarcity of literature on ChatGPT use for academic dishonesty, there is an evidence gap arising from the conflicting findings among previous studies. These gaps justify considering sex as a control variable in the present study, leading to the formulation of the following hypotheses:

H_5: The direct effect of perception on students' attitudes toward using ChatGPT for academic dishonesty does not significantly vary with student sex.
H_6: The direct effect of students' perceptions of their actual use of ChatGPT for academic dishonesty does not significantly vary with sex.
H_7: The direct effect of attitude on students' actual use of ChatGPT for academic dishonesty does not significantly vary with sex.
H_8: There is no significant sex-based variation in the mediating effect of attitude on the relationship between perceptions and students' use of ChatGPT for academic dishonesty.

2.5 Age differences

Scholars have established that there are differences in terms of age in the perception and utilisation of ICT among students. Indeed, scholarly discourse contends that younger students demonstrate superior proficiency in utilising information and communication technology (ICT) compared to their older counterparts

(Odigwe & Owan, 2020; Ozimek & Bierhoff, 2016). However, other studies have shown no difference in this nexus (Dúo-Terrón et al., 2022; Juhaňák et al., 2019; Owan & Asuquo, 2021; Owan et al., 2021). This finding implies that there are also contradictory findings among scholars about age and the utilisation of ICT. It is important to state that, apart from the contradictory findings, studies that focus specifically on these variables concerning how they influence academic dishonesty using artificial intelligence tools such as the ChatGPT are rare or nonexistent at the time of writing. Thus, the following hypotheses were formulated:

H_9: The direct effect of perception on students' attitudes toward using ChatGPT for academic dishonesty does not significantly differ with age.
H_{10}: The direct impact of students' perceptions of ChatGPT on their actual use of ChatGPT for academic dishonesty does not significantly differ with age.
H_{11}: The direct impact of attitude on students' actual use of ChatGPT for academic dishonesty does not significantly differ with age.
H_{12}: There is no significant age-based variation in the mediating effect of attitude on the relationship between perceptions and students' use of ChatGPT for academic dishonesty.

2.6 Conceptual framework

The linkage between the variables is presented in Fig. 1.

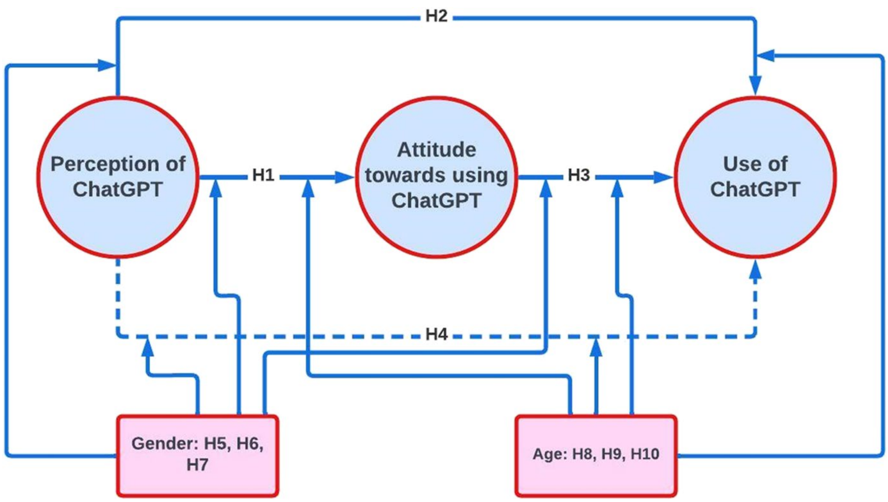

Fig. 1 Conceptual framework of the study: Direct effects = solid lines; mediation effect = dashed line

3 Methodology

3.1 Participants

A cross-sectional research design was adopted for this study. The design was suitable since the researchers collected data from various sources at a particular time to better understand the nature of the relationships among the variables. The study sample comprised higher education students with AI tools available on a laptop or phone. The study included 4679 students from 13 universities in the study area. The demographic characteristics of the participants included 1820 (38.8%) males and 2877 (61.2%) females. In terms of age, 1592 (34.02%) were younger than 25 years, 1788 (38.21%) were between 25 and 35 years, and 1299 (27.76%) were 36 years and older. For marital status, 2230 (47.66%) were single, 1117 (23.87%) were married, and 1332 (28.46%) were either divorced or separated.

3.2 Measures and instrument

There are five key variables in this study, which include sex, age, perception, attitude, and utilisation of the ChatGPT for academic dishonesty. In this study, sex was defined as the biological feature that separates people into males or females. Age is conceptualised as the number of years a person has lived. Thus, respondents indicated their age by ticking one of three age categories: below 25, 25–35 years, or 36 years or older. Perception refers to students' feelings or mindsets about AI tools for promoting academic dishonesty. Attitudes towards the ChatGPT are defined as students' dispositions towards the tool. Using AI tools for academic dishonesty tends to misapply these tools to unethical activities.

A structured questionnaire, developed by the researchers, served the purpose of data collection. In section A of the questionnaire, demographic information about the respondents, such as sex, age, and marital status, was collected. Section B contained six items to collect data on students' perceptions of and use of the ChatGPT for academic dishonesty. The items in this section were modified from previous studies (Chawla et al., 2023; Grassini, 2023), and one sample item is ''*I sometimes feel that using ChatGPT for my academics is very unethical'*. Similarly, section C collected data about students' attitudes toward using ChatGPT for academic dishonesty; the scale included six items. The items in section C were adapted from previously validated instruments (Ahmad et al., 2023; Jang et al., 2022) and modified to suit higher education students in the Nigerian context. A sample item in section C is ''*I do not find using ChatGPT for anything academics interesting*.'' The adaptation was done to suit the cultural and contextual relevance, clarity, and appropriateness of the target population while still ensuring the validity of the item. Similarly, some terms that were commonly used in Nigeria, like 'schoolwork' instead of 'assignments', among others, were modified to suit what the respondents can easily understand. Section D elicited information on the utilisation of ChatGPT for academic dishonesty. Six items were adapted from the questionnaire developed by Sallam et al. (2023) to collect the data. Nevertheless, various unethical practices of students, such as direct copying and pasting from ChatGPT, attributing text generated by ChatGPT to inappropriate sources, and translating text generated by ChatGPT to other languages, were listed while using ChatGPT. All the items in sections B to D of the questionnaire were organised on a four-point Likert scale of agreement. The response options ranged from strongly agree to strongly disagree.

The items in the instrument were validated using three experts in educational technology and three psychometric experts, all of whom were professors with more than 10 years of experience. The purpose was to quantitatively determine the suitability, precision, and representativeness of the items. The initial questionnaire was made up of 30 items and each construct was measured using 10 items. That is for students' perception of ChatGPT($n=10$), attitude to ChatGPT($n=10$) and utilization of ChatGPT for academic dishonesty($n=10$). A copy of the instrument with the research questions and background to the study was given to the experts to have basic knowledge of what the study sought to achieve. The researchers designed a rubric following the recommendations of experts on how to determine the quality of items using measures like precision, representativeness, and clarity, among others (See Yusuf, 2019). However, in this study, only two criteria were used. Each expert was asked to rate the items on a Likert scale from 1 (Not relevant) to 4 (Very relevant). The criteria for evaluation included precision and representativeness of each item. The scoring of 1 and 2 by experts means that the item is not relevant and 3 and 4 imply that it is relevant. The experts' ratings aided in the computation of item content validity indices (I-CVI) and scale content validity indices (S-CVI). The I-CVI ranged from 0.78–0.87, 0.79–0.91 (precision) and 0.82–0.87 (representativeness). Items with an index less than 0.70 were removed, as suggested by experts (Owan et al., 2023a; Zamanzadeh et al., 2015). Similarly, for the scale content validity indices (S-CVI), the range of items was 0.91–0.98 for suitability, 0.92–0.98 for precision, and 0.91–0.97 for representativeness. These quantitative measures helped to reduce the number of items from 30 to 17 that were used finally for the study.

3.3 Ethical considerations and data collection

As a survey study, ethical clearance was waived per national regulations (See Federal Ministry of Health, 2007) since it does not pose any physical or psychological harm to the respondents. However, the researchers indicated in the instrument that it is not compulsory for respondents to participate in the study. This was why a check box was provided for respondents to provide written informed consent before participating. The respondents were also informed that the solicited data would be used for publication in a peer-reviewed journal after anonymising self-identifying information and aggregating all the data.

The researchers collected the data electronically with the help of different class administrators at the various universities selected for this study. A total of 50 research assistants, who were financially rewarded, supported the researchers in collecting data for the study. First, the researchers were able to identify class representatives through these research assistants, who were informed of the exercise and were to discuss it with the class representatives before the arrival of the team for final interaction and briefings. At the end of the interaction and after the purpose of the study, their role in the study, and what is expected of them, a copy of the instrument was sent to various platforms. A total of 1,032 class representatives were spoken from various departments. These class representatives were added to the Telegram group created by the researchers to help them share the instrument strictly on their various class platforms. A comma separated values (.csv) file was created for responses to be obtained electronically from those who completed and submitted their responses. The compulsory options in Section A were asterisks to obtain the students' demographic information regarding their sex and age. The administration and collation of the data took ten months (February 2023 to November 2023). A total of 4504 students' responses were ultimately obtained for the study. A variance approach to structural equation modelling was employed to test the earlier hypothesised model. The results of the analysis are presented in the following section.

4 Results

The results of this study are reported in two parts: the measurement model and the structural model. The measurement model provides a report of the data quality criteria and construct validity evidence, as well as the reliability indices of each variable (Owan et al., 2022). On the other hand, the structural model provides an empirical test of the hypothesised model regarding the various predictions among constructs in the model (Owan et al., 2023a).

4.1 Measurement model and quality criteria assessment

Table 1 shows that all the factor loadings of the items in the model were high for their respective factors. The literature has suggested that items with loadings above 0.70 are desirable (Memon & Rahman, 2014). Table 1 shows that all the values of the item loadings are above 0.70, suggesting that all the items meet the minimum requirements. At the scale level, the Cronbach's alpha and composite reliability values are greater than 0.70 for all the constructs, implying evidence of internal consistency for each variable.

The average variance extracted (AVE) was used to determine whether convergent validity was achieved in the measurement models. It is common knowledge that an AVE value of 0.50 or higher is sufficient evidence for convergent validity for a construct. Table 1 shows that convergent validity was achieved for all the variables.

It was important first to identify any potential collinearity within the structural model, a factor that could introduce bias into the path coefficients. Table 1 indicates that the outer variance inflation factors (VIFs) for all the constructs did not exceed the threshold of 5.00 recommended by scholars (Hair et al., 2017), ranging from 1.54 to 5.00. Similarly, the VIFs for the inner model did not exceed 5.00, ranging from 1.00 to 1.05 (see Table 1). This finding suggested that there was no significant collinearity among the predictor constructs in the structural model.

Table 1 Quality criteria assessment of the constructs underlying the study

Constructs/Indicators	α	CR	AVE	λ	VIF	R^2	f^2	$Q^2_{predict}$
Perception of ChatGPT	.90	.94	.83		1.00		.034	
PER1				.90	3.11			
PER2				.89	2.69			
PER4				.95	5.00			
Attitude towards ChatGPT	.86	.89	.63		1.05	.045	.047	.044
ATT1				.82	1.54			
ATT3				.81	1.95			
ATT4				.79	2.02			
ATT5				.76	2.17			
ATT6				.78	2.14			
Utilisation of ChatGPT	.89	.92	.69		1.05	.070	.057	.037
UTI1				.86	3.64			
UTI4				.79	2.06			
UTI5				.83	2.24			
UTI8				.91	3.06			
UTI9				.75	2.70			

Second, we examined the proportion of variance in the endogenous variables explained by the exogenous variables to ascertain the model's in-sample model fit and predictive accuracy. Table 1 shows that perception explains 4.5% ($R^2 = 0.045$) of the variance in the students' attitudes toward using ChatGPT for academic dishonesty. Similarly, perception and attitude jointly explained 7.0% ($R^2 = 0.070$) of the variance in students' utilisation of ChatGPT for academic dishonesty. Thus, 95.5% and 93% of the variance were in the attitudes toward and utilisation of ChatGPT, respectively, for academic dishonesty. According to the established rules, the model's predictive accuracy may be weak. Scholars have recommended acceptable R^2 values of 0.10 or above (Hair et al., 2013). Nevertheless, the relatively weak R^2 is due to the model complexity (involving a few numbers of predictors). We accepted the model because, in the behavioural sciences, various factors can explain the variance in an endogenous variable, such that a single variable should not be expected to explain as much as 10% of the variance. This also aligns with the decision made by Hair et al. (2017), specifically in chapter 6 of their book. The f^2 values reported in Table 1 range from 0.034 to 0.057, indicating small effect sizes (Cohen, 1988).

4.2 Discriminant validity

Discriminant validity was assessed to ensure that theoretically unrelated variables were correlated at a high level. There are various approaches to ascertaining the discriminant validity of constructs. One popular method is the Fornell–Larcker approach (Fornell & Larcker, 1981), where the square of the AVE is compared with the correlation of a factor to other factors in the model (Owan et al., 2022). Table 2

Table 2 Discriminant validity evidence through the Fornell–Larcker and HTMT approaches

Variables	(1)	(2)	(3)
Attitude (1)	**0.792**	*0.218*	*0.192*
Perception (2)	0.212	**0.913**	*0.229*
Utilisation of ChatGPT (3)	-0.133	0.196	**0.829**

Square roots of AVE are bolded along the diagonal; HTMT values are above the diagonal in italics; Factor correlations are below the leading diagonal

shows that discriminant validity was achieved for the three constructs, as the bolded values along the diagonal (square root of the AVE) are greater than the correlation coefficients below them. Another approach to ascertain whether discriminant validity was achieved is the heterotrait-to-trait ratio (HTMT). As a rule, HTMT values must be less than 0.90 (Owan et al., 2022). As shown in Table 2, all the HTMT values above the leading diagonal are well below the threshold of 0.90, further providing evidence of discriminant validity from another lens.

To examine the "out-of-sample" model fit, we employed PLSpredict with 10 folds and a single repetition to replicate how the PLS model would be utilised for predicting a new observation, avoiding using averages across multiple models. This procedure uses training and holdout samples to estimate model parameters and evaluate predictive power separately (Sharma et al., 2023). Consequently, we constrained a portion of the dataset as the training sample to estimate crucial parameters, while the remaining data constituted the holdout sample for predictive purposes. Model estimates from the training sample were subsequently applied to predict dependent construct indicators (Shmueli et al., 2019), enabling an evaluation of prediction accuracy at the indicator or composite score level for a comprehensive assessment of predictive power.

The Q^2 values obtained from the PLSpredict procedure ranged from 0.044 to 0.037, indicating positive values greater than zero (Table 1). A Q^2 value above zero indicates good reconstruction, demonstrating that the model has predictive relevance. Moreover, in instances where the Q2 value is positive, the predictive error of PLS-SEM outcomes is less than that of employing mean values alone, thereby indicating the superior predictive performance of PLS-SEM (Hair et al., 2022; Shmueli et al., 2019). Subsequently, a more detailed examination of the prediction errors was conducted to determine the pertinent prediction statistics. The graphical representations in Fig. 2 indicate that the PLS-SEM errors are not normally distributed. Consequently, the mean absolute error (MAE) was preferred over the root mean squared error (RMSE) for evaluating the predictive power of the model (due to the nonsymmetric distributions shown in Fig. 2).

Upon comparing the MAEs derived from the PLS-SEM analysis with those of the naïve linear regression (LM) benchmark (as presented in Table 3), it is evident that the PLS-SEM analysis yielded the same scores as did the LM approach for most items, such as ATT1, ATT4, ATT6, ATT3, UTI4, and UTI1. However, the PLS-SEM procedure yielded slightly greater MAEs than did the LM procedure for items ATTI5, UTI9, UTI8, and UTI5; these differences were not significant, ranging from

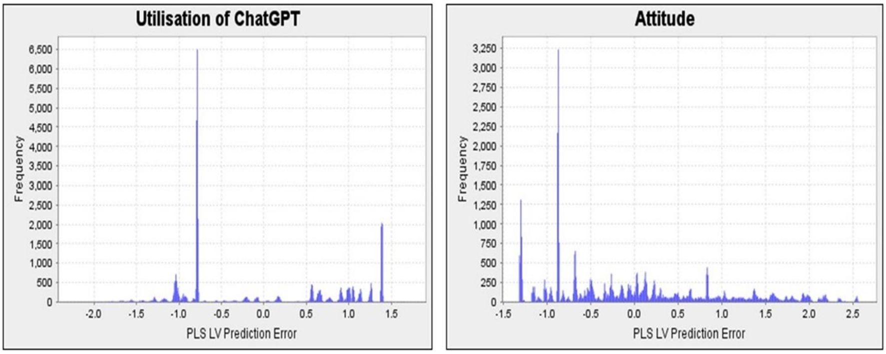

Fig. 2 Histogram plots showing the distribution of the endogenous variables

Table 3 Predictive model fit assessment using the MAEs derived from the PLS-SEM and LM procedures

Items	PLS-SEM		LM		PLS-SEM – LM MAE
	MAE	$Q^2_{predict}$	MAE	$Q^2_{predict}$	
ATT1	0.62	0.05	0.62	0.06	0.00
ATT4	0.69	0.01	0.69	0.02	0.00
ATT6	0.68	0.02	0.68	0.02	0.00
ATT5	0.63	0.02	0.62	0.02	0.01
ATT3	0.63	0.02	0.63	0.02	0.00
UTI9	0.47	0.01	0.46	0.03	0.01
UTI4	0.63	-0.05	0.62	0.01	0.00
UTI8	0.51	0.07	0.49	0.09	0.01
UTI1	0.47	0.02	0.47	0.02	0.00
UTI5	0.50	0.05	0.48	0.08	0.02

0.01 to 0.02. Considering that the PLS-SEM contains a mediating variable, unlike in the LM model, the minor deviations in the MAEs may provide evidence of a predictive model, especially as all the other quality criteria provide adequate support (ShmuelI et al., 2019).

4.3 Structural model and test of hypotheses

The hypotheses of this study were tested in line with the conceptual model to determine the direct and indirect effects of students' perceptions and attitudes on their utilisation of ChatGPT for academic dishonesty. Figure 3 shows that students' perceptions and attitudes collectively contribute 7.0% to the variation in their utilisation of ChatGPT for academic dishonesty ($R^2=0.070$, $p<0.001$). Similarly, students' perceptions accounted for 4.5% of the variance in their attitudes toward using ChatGPT for academic dishonesty ($R^2=0.045$, $p<0.001$).

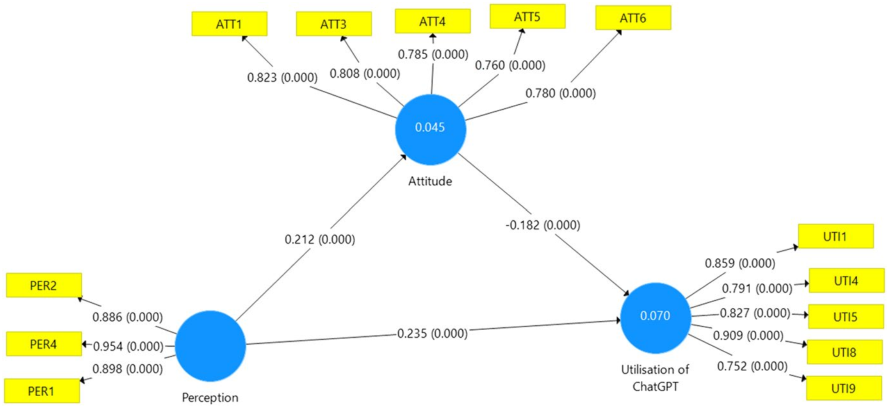

Fig. 3 PLS structural equation model showing the relationships among perceptions, attitudes and use of ChatGPT for academic dishonesty

Table 4 reveals that the direct effect of perception on students' attitudes toward using ChatGPT for academic dishonesty (H_1) is statistically significant ($\beta = 0.21$, $p < 0.001$). Table 4 also shows a significant direct effect of perception on students' actual use of ChatGPT for academic dishonesty ($\beta = 0.24$, $p < 0.001$). Similarly, a significant negative direct effect of attitude on students' use of ChatGPT for academic dishonesty was revealed, $\beta = -0.18$, $p < 0.001$). Furthermore, Table 4 reveals that attitude has a significant negative mediating effect on the relationship between students' perceptions and their actual use of ChatGPT for academic dishonesty (β=-0.04, $p < 0.001$). Thus, according to the results in Table 4, our first four hypotheses (H_1, H_2, H_3, and H_4) are supported.

4.4 Demographic differences in the direct and mediation effects

The first four hypotheses reported in Table 5 were further tested. A multigroup analysis was performed to determine whether there were sex- or age-related differences in direct and mediation effects that were previously reported. Table 5 shows that the direct effect of students' perceptions of their attitudes toward using ChatGPT for academic dishonesty is significantly positive for both females ($\beta = 0.191$, $p < 0.01$) and males ($\beta = 0.27$, $p < 0.001$), with a nonsignificant difference (δ=-0.075, $p > 0.05$).

Table 4 Direct and mediation effects of the three measures

Hypotheses	M	SD	β	[95% CI]	*t*	*p*	Decision
H_1: Perception → Attitude	0.21	0.02	.21	.18, .24	13.20	.000	Supported
H_2: Perception → ChatGPT use	0.24	0.03	.24	.19, .29	9.54	.000	Supported
H_3: Attitude → ChatGPT use	-0.18	0.03	-.18	-.23, -.09	5.32	.000	Supported
H_4: Perception → Attitude → ChatGPT use	-0.04	0.01	-.04	-.05, -.02	5.21	.000	Supported

Table 5 Multigroup analysis for sex differences

Sex	Paths coefficients	M	SD		β	t	p
Females	Perception → Attitude	0.22	0.07		0.19	2.75	.006
	Perception → ChatGPT use	0.14	0.14		0.20	1.42	.157
	Attitude → ChatGPT use	-0.21	0.05		-0.21	4.17	.000
	Perception → Attitude → ChatGPT use	-0.45	0.02		-0.04	1.76	.078
Males	Perception → Attitude	0.27	0.04		0.27	7.37	.000
	Perception → ChatGPT use	0.37	0.02		0.37	17.66	.000
	Attitude → ChatGPT use	-0.21	0.05		-0.21	4.28	.000
	Perception → Attitude → ChatGPT use	-0.06	0.02		-0.06	3.41	.000
Difference	Hypotheses	Coefficient (β)			δ	p	Decision
		Baseline	Female	Male			
	H_5: Perception → Attitude	.21	0.19	0.27	-0.08	.160	Supported
	H_6: Perception → ChatGPT use	.24	0.20	0.37	-0.17	.027	Not supported
	H_7: Attitude → ChatGPT use	-.18	-0.21	-0.21	0.01	.872	Supported
	H_8: Perception → Attitude → ChatGPT use	-.04	-0.04	-0.06	0.02	.250	Supported

Similarly, Table 5 shows that the direct effect of perception on students' ChatGPT use for academic dishonesty is nonsignificantly positive for females ($\beta = 0.203$, $p > 0.05$) but significantly positive for males ($\beta = 0.372$, $p < 0.001$). The permutation test revealed a significant difference ($\delta = -0.169$, $p < 0.05$) between males and females regarding the direct effect of perception on students' ChatGPT use for academic dishonesty. Moreover, Table 5 reveals that students' attitudes have a negative and significant direct effect on their ChatGPT use for academic dishonesty for both females ($\beta = -0.205$, $p < 0.001$) and males ($\beta = -0.212$, $p < 0.001$), with a nonsignificant sex difference ($\delta = 0.007$, $p > 0.05$).

Additionally, Table 5 reveals that attitude has an insignificant negative mediating effect on the relationship between students' perceptions and their actual use of ChatGPT for academic dishonesty for females ($\beta = -0.039$, $p > 0.05$), whereas for males, the mediating effect is significantly negative ($\beta = -0.056$, $p < 0.001$). However, the permutation test revealed a nonsignificant difference ($\delta = 0.017$, $p < 0.001$) in the mediating effect of attitude between male and female students. As shown in Table 5, hypotheses five, seven and eight were supported, whereas hypothesis six was not supported. It was also revealed that perception and attitude, when combined, explained 6.7% of the variance ($R^2 = 0.067$) in male students' ChatGPT use for academic dishonesty, while in females, 14.1% of the variance was explained. Similarly, perception explained 3.7% of the variance in male students' attitudes toward using ChatGPT for academic dishonesty, while 7.71% of the variance was explained for females.

To verify whether the hypotheses of this study were stable across students of different age categories, a multigroup analysis was performed, and the results are summarised in Table 6. Table 6 reveals a significant positive direct effect of students' perceptions on their attitudes toward using ChatGPT for academic dishonesty for those aged younger than 25 years (β = 0.27, $p < 0.001$) and those aged 25–35 years (β = 0.24, $p < 0.001$). However, for individuals aged 36 years and above, although the direct effect is positive, it is deemed statistically insignificant (β = 0.11, $p > 0.05$). Nonetheless, there were no statistically significant differences in age concerning the direct effect of perception on students' attitudes toward using ChatGPT for academic dishonesty.

Table 6 also indicates that perception has an insignificant direct effect on students' ChatGPT use for academic dishonesty among students younger than 25 years (β = 0.13, $p > 0.05$). However, for students aged 25 to 35 years (β = 0.17, $p < 0.001$) and those aged 36 years or older (β = 0.299, $p < 0.001$), the direct effect of perception was significantly positive for their use of ChatGPT for academic dishonesty. Multiple pairwise comparisons revealed no significant age differences in terms of the direct effect of perception on students' ChatGPT use for academic dishonesty. Table 6 further reveals that students' attitudes have a significant positive direct effect on their ChatGPT use for academic dishonesty among individuals younger than 25 years (β = 0.34, $p < 0.001$). However, there was a significant negative direct effect for those aged 25–35 years (β = -0.27, $p < 0.001$) and those aged 36 years and above (β = -0.25, $p < 0.001$). The permutation test indicated no significant age differences in the direct effect of attitude on students' ChatGPT use for academic dishonesty.

Table 6 indicates that the mediating effect of attitude on the relationship between students' perceptions and their actual use of ChatGPT for academic dishonesty is positively significant for students younger than 25 years (β = 0.093, $p < 0.001$) but significantly negative for those aged 25–35 years (β = − 0.07, $p < 0.001$). However, the mediation effect is insignificantly negative for students aged 36 and above (β = 0.02, $p > 0.05$). Nevertheless, the permutation test revealed that the mediating effect of attitude on linking students' perceptions to their actual use of ChatGPT did not significantly vary across all pairwise comparisons. Based on these results, hypotheses 9, 10, and 11 were supported. In contrast, hypothesis 12 was not supported. In addition, it was discovered that perception and attitude jointly explained 16.1, 9.2, and 13.7% of the variance in students' ChatGPT use for academic dishonesty among students younger than 25 years ($R^2 = 0.161$), 25–35 years ($R^2 = 0.092$), and 36 years or older ($R^2 = 0.13$), respectively. Furthermore, the results indicated that student perceptions were responsible for 1.1, 5.8 and 7.3% of the variance in attitudes toward using ChatGPT for academic dishonesty among respondents younger than 25 years ($R^2 = 0.011$) between 25 and 35 years ($R^2 = 0.058$) and 36 years or older ($R^2 = 0.073$), respectively.

5 Discussion of findings

This study examined how attitude mediates the relationship between students' perceptions and their actual use of ChatGPT for academic dishonesty. The researchers also tested for sex- and age-specific differences in the tripartite relationship among

Table 6 Multigroup analysis for age variations

	Below 25yrs age (G1)			25 to 35 years (G2)			36 years and above (G3)		
Paths	β	*t*	*p*	β	*t*	*p*	β	*t*	*p*
Perception → Attitude	.27	6.41	.000	0.24	6.49	.000	0.11	0.93	.345
Perception → ChatGPT use	.14	1.31	.120	0.17	4.78	.000	0.30	7.38	.000
Attitude → ChatGPT use	.34	6.36	.000	-0.29	15.04	.000	-0.25	7.67	.000
Perception → Attitude → ChatGPT use	.09	3.26	.000	-0.07	5.90	.000	-0.03	1.01	.186
Test of differences	Baseline			Pairwise permutation test					
Hypotheses	G1	G2	G3	G1 vs G2		G1 vs G3		G2 vs G3	
				δ	*p*	δ	*p*	δ	*p*
Perception → Attitude	.34	-.29	-.25	.002	> .05	.009	> .05	.001	> .05
Perception → ChatGPT use	.27	.24	.11	.001	> .05	.001	< .05	-.001	> .05
Attitude → ChatGPT use	.14	.17	.30	-.001	> .05	.002	> .05	.002	> .05
Perception → Attitude → ChatGPT use	.09	-.07	-.03	.001	< .001	.001	< .001	.001	< .05

the three variables. Based on the results presented and interpreted in the preceding section, the key findings are as follows:

5.1 Perception and attitudes toward using the ChatGPT

We discovered through this study that students' views about ChatGPT strongly influence their attitudes toward using it for academic dishonesty. This finding held for both male and female students across different age groups. In other words, regardless of sex or age, students' perceptions of ChatGPT was linked to their overall attitude toward using it unethically in academics. This means that students who had a positive view of the ChatGPT were more likely to be open to using it for academic dishonesty, regardless of their age or sex. These findings suggest that students' perceptions of ChatGPT universally influence their attitudes toward its unethical use by academics, transcending sex and age differences. Previous research has provided evidence that students' perceived ease of use and usefulness of artificial intelligence is highly important for their intentions to use such technology (Kashive et al., 2020; Shamsi et al., 2022). Thus, the present study's findings could indicate that attitudes toward academic dishonesty involving the ChatGPT are more strongly shaped by common perceptions and beliefs about the tool's capabilities than by individual demographic factors.

5.2 Perception and students' ChatGPT use

This study revealed a positive direct effect of students' perceptions of ChatGPT on their use of ChatGPT for academic dishonesty. Interestingly, this effect was more pronounced among female students than among male students. However, regarding student age, the findings are mixed. No significant difference was recorded in the direct effect in comparisons, such as students aged under 25 versus those aged 25 to 35 or those aged 25 to 35 versus those aged 36 or older. However, there was a notable difference between students under 25 and those aged 36 or older, with the effect being stronger for the younger group. The sex difference in the positive direct effect of perception on ChatGPT use for academic dishonesty suggested that female students may be more susceptible to the influence of their perceptions of engaging with the tool unethically than their male counterparts are. This could be attributed to various factors, including differential attitudes toward technology, academic pressure, or social dynamics. Previous research has shown that student awareness, attitude, and willingness to use technology are crucial for actual use (Owan & Robert, 2019; Owan et al., 2023a; Petters et al., 2024). Moreover, other studies have shown that different students accept technology differently (Sprenger & Schwaninger, 2021; Staddon, 2020), resulting in potential differences in their actual use for various purposes.

Nevertheless, the mixed age-related findings add an interesting layer to the study. While there was no significant difference in the direct effect between specific age groups, the notable difference between students younger than 25 and those aged 36 or older suggested a generational impact. The stronger effect observed in the younger group may reflect a higher comfort level or familiarity with technology, potentially influencing their decisions to use ChatGPT for academic dishonesty. This finding agrees with the findings of other previous studies that have generally associated the high use of technology among younger students with their high level of familiarity and immersion in the latest ICT trends (Owan & Asuquo, 2021; Owan et al., 2021; Petters et al., 2024).

Overall, the positive direct effect discovered in the present study implies that students who had a positive opinion about ChatGPT were more likely to use it for academic dishonesty. Thus, their perception of ChatGPT directly influenced their decision to engage in dishonest academic behaviour. One possible explanation for this finding is that students with a positive perception of ChatGPT may view it as a tool to help them achieve better academic outcomes with less effort. Various studies have documented various factors that motivate students to use the ChatGPT in academic settings, including perception-related variables, such as timesaving ability, self-efficacy, skepticism, self-esteem, and perceived stress (Bin-Nashwan et al., 2023; Singh et al., 2023). The perceptions of students might lead them to consider using the ChatGPT for academic dishonesty, seeing it as a shortcut to success. This finding aligns with several previous studies that have revealed various sharp practices that students indulge in that are traceable to their perceptions (Eneji et al., 2022; Owan et al., 2023c, 2023d).

Another explanation could be that students who have a favourable opinion of the ChatGPT may believe that using it for academic dishonesty is a socially acceptable behaviour, perhaps because they see it as a common practice among their peers. It has been proven that social influences can significantly shape individuals' behaviours, and a positive perception of ChatGPT may contribute to the normalisation of dishonest academic practices (Kikerpill & Siibak, 2023; Ray, 2023). Additionally, students who trust the effectiveness of the ChatGPT might be more confident in their ability to use it without being caught, further influencing their decision to engage in academic dishonesty. A perceived low risk of detection could be a motivating factor for those who have a positive opinion about the tool.

5.3 Attitude and students' ChatGPT use

This study revealed a significant negative direct effect of attitude on students' ChatGPT use for academic dishonesty. Moreover, there were no significant sex- or age-related differences in the direct effect of attitude on students' ChatGPT use for academic dishonesty. In other words, regardless of sex and age, a negative attitude had a similar inhibitory impact on academics' likelihood of using the ChatGPT unethically. This finding implies that when students have a negative attitude toward using ChatGPT for academic dishonesty, they are less likely to use it for cheating in academics. Therefore, a more negative attitude was associated with a decreased likelihood of using ChatGPT for dishonest academic purposes. Various explanations can be provided for this finding. Students with a negative attitude toward using ChatGPT for academic dishonesty may have a strong moral compass. They might perceive cheating as ethically wrong and incompatible with their values, leading them to resist using ChatGPT for dishonest academic purposes. A negative attitude toward cheating might reflect a commitment to upholding these internalised norms, making them less likely to use ChatGPT for dishonesty. This finding strengthens the findings of previous studies revealing the positive influence of moral values on decreasing social vice and unacceptable behaviours among students (Crawford et al., 2023; Huallpa et al., 2023; Stahl & Eke, 2024). In addition, previous research (e.g., Hosseini et al., 2023) has shown that most students' attitudes toward AI are negative. Thus, drawing from the present study's findings, students with a negative perception could be concerned about the academic and disciplinary repercussions of using ChatGPT for cheating, leading them to avoid such behaviour to mitigate potential risks. The prevailing attitudes within a student's social and academic environment can also play a role. Several previous studies have shown that the propagation of social stigma against academic dishonesty and a collective negative attitude within their peer group or society may influence students to align their behaviour accordingly (Mattar, 2022; Smith et al., 2021).

5.4 The mediating role of attitude in linking perception to students' ChatGPT use

It was discovered in this study that student attitude has a significant negative mediating effect on the relationship between perception and student ChatGPT use for academic dishonesty. This mediating effect was consistent for both male and female students. However, the effect varied with age; the mediating effect was strongest for students younger than 25 years, followed by those aged 25 to 35 years, and weakest for those aged 36 years or older. In essence, younger students showed a stronger influence of attitude in shaping their use of ChatGPT for academic dishonesty than older students did. The consistent negative mediating effect of attitude across both sexes suggested a universal role of attitude in influencing students' decisions regarding ChatGPT use for academic dishonesty. This highlights the importance of cultivating acceptable attitudes among students, which acts as a mediator regardless of sex. However, the stronger mediating effect observed for students younger than 25 years suggested that attitudes play a more decisive role in shaping their behaviour concerning ChatGPT. This could be attributed to a more malleable ethical framework, greater exposure to social media, greater susceptibility to peer influence, or stronger connections between personal values and decision-making in the younger age group. On the other hand, the weaker mediating effect in students aged 36 or older may indicate a more established and stable ethical framework or a reduced reliance on attitudes when making decisions about academic dishonesty. These findings corroborate the findings of other studies that have associated students' propensity to use ChatGPT, AI or ICT with various factors, such as awareness, willingness, peer group, and social acceptance (Owan et al., 2023a; Petters et al., 2024; Prashar et al., 2023).

The findings of this study indicate that students' attitudes, as a mediator, significantly altered the effect of perception, reducing the likelihood that their positive perception would lead them to use the ChatGPT for dishonest academic purposes. This finding can be explained by the fact that students with a positive perception of the ChatGPT may initially see it as a valuable tool for academic assistance. However, if their attitudes are strongly aligned with ethical considerations, they may reconsider using the tool for dishonest purposes, countering positive perceptions. These findings agree with several existing studies that have established a strong link between students' attitudes toward, perceptions of and use of AI (Kapania et al., 2022; Nguyen & Crossan, 2022). Moreover, the discrepancy between a positive perception and a negative attitude may create internal conflict within students. The cognitive dissonance arising from the conflict between their favorable view of ChatGPT and their ethical stance could lead to a resolution to maintain academic integrity, reducing the likelihood of using the tool for dishonesty. In addition, previous research has shown that the attitudes of peers and societal norms surrounding academic honesty may also play a role (Bin-Nashwan et al., 2023; Vučković et al., 2020). Thus, if students observe that their peers with positive perceptions maintain negative attitudes toward using ChatGPT for dishonesty, this could influence their attitudes and behaviour, creating a collective deterrent effect.

6 Limitations of the study

This study, like its counterparts, is not exempt from inherent limitations. First, its scope is exclusively confined to examining ChatGPT utilisation within Nigerian public universities, thereby precluding consideration of private institutions. Consequently, its applicability and generalisability to alternative contexts remain uncertain. To rectify this deficiency, future investigations should broaden their scope to encompass private institutions, thereby facilitating a comprehensive assessment of ChatGPT's utilisation concerning academic integrity. Additionally, the susceptibility of this study to respondent biases and prejudices is noteworthy, given its reliance on self-reports during data collection. This approach poses the risk of respondents inaccurately reporting their experiences. Incorporating alternative methodologies, such as observational techniques, could enhance the study's reliability and objectivity. It is imperative to highlight that these identified limitations, notwithstanding, do not render the study's findings invalid or inconsequential. In contrast, the present study provides valuable information to the existing body of knowledge on perceptions, attitudes, and utilisation of ChatGPT among Nigerian students. Thus, further research could add, update, refine or expand upon this study's scope, weaknesses and strengths.

7 Theoretical/practical implication of the study

The findings of the study hold both theoretical and practical implications of the study. The findings of the study hold both theoretical and practical implications. Theoretically, the findings provide valuable information that aids in the understanding of how student's perceptions and attitudes affect the use of ChatGPT for academic dishonesty among higher education students. This is an advantage to theoretical models like Technology Acceptance Models (TAM) and Theory of Planned Behaviour in explaining better what attitude can facilitate in the learner. It also provides opportunities for the inclusion of gender and other generational factors that can be incorporated into theoretical models developed to explain technology behaviour among different groups of people. This is because different groups respond to technology in different ways. Incorporating these differences in the theoretical model can facilitate interventions suitable for inclusivity and equity.

Practically, the study also holds some implications for educators and policymakers to arrest issues of dishonesty through the use of technology like ChatGPT. First, interventions that address students' perceptions and attitudes towards technology can be developed through orientations and workshops in order to promote the ethical use of these tools. Policies and measures that will deter students from utilizing these tools for unethical purposes should be implemented with clear guidelines on the ethical use of AI tools. Tailored approaches based on gender and age should be adopted to ensure that educational programmes that integrate technology ethics into the curriculum facilitate the responsible use of AI and adherence to digital ethics.

8 Conclusion

This study assessed the relationship between students' perceptions, attitudes, and use of ChatGPT for academic dishonesty. The findings underscore the significant role of perception in shaping students' attitudes toward and subsequent use of the ChatGPT. Regardless of sex or age, academic students with positive views of the ChatGPT were more inclined to consider using it unethically. Interestingly, the present study revealed a sex difference in the direct effect of perception on ChatGPT use, with female students showing a more pronounced influence. On the other hand, the age-related differences, particularly the stronger effect observed in younger students, suggest a generational impact. Younger students may exhibit greater comfort and familiarity with technology, influencing their decisions to engage in academic dishonesty using the ChatGPT. The negative direct effect of attitude on students' ChatGPT use for academic dishonesty implies that students with a more negative attitude were less likely to resort to unethical practices. This negative attitude may be rooted in a strong moral compass and ethical considerations, acting as a deterrent against cheating. Furthermore, the study identified attitude as a significant negative mediator of the relationship between perception and ChatGPT use. This mediating effect was consistent across sexs but varied with age, being strongest for younger students. The mediation results suggest that attitudes play a crucial role in mitigating the impact of positive perceptions, leading to a more ethical decision-making process. Overall, this study contributes valuable information to the literature regarding the interplay of perceptions, attitudes, and actual behaviour concerning ChatGPT use in academic settings. This study emphasises the importance of fostering positive attitudes among students, especially younger ones, as a potential counterbalance to the allure of using ChatGPT for dishonest academic purposes. The study also underscores the need for educational institutions and policymakers to address these issues and promote ethical behaviour in the rapidly evolving landscape of artificial intelligence in education. Hence, as Nigeria strives to integrate AI fully into its educational curriculum, it is imperative not to overlook the necessity of educating students on the potential benefits of AI for their academic pursuits.

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Author contributions All the authors contributed adequately to the study.

Data availability The authors declare that the data of this study are available on request from the corresponding author.

Declarations

The authors declare this an original research study and not material obtained elsewhere.

Ethical approval Ethical approval was waived for this study since there was no potential danger or risk in participation, as per the national guidelines.

Consent to participate The consent to participate in this study was obtained from all participants. There was an explicit agreement between the researcher and the participants that their data shall only be aggregated without disclosing personal identities. The analysis and presentation of results were also treated aggregately based on the agreement reached with the participants.

Consent for publication All the participants agreed that the researchers could publish the information so long as they are treated with confidentiality, without disclosing their identities.

Competing interests The authors declare no competing interests in this study.

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