Article

Volume 15, Issue 4 (2026), pp. 83-106
Journal of Interdisciplinary Studies in Education
ISSN: 2166-2681Print 2690-0408 Online | https://ojed.org/jise
https://doi.org/10.32674/nq9swx67

The Digital Facilitator: A Multivariate Analysis of Predictors of Academic Cheating

Abel Ebiega Enokela
Federal College of Education, Ofeme-Ohuhu, Nigeria

Caroline Ochuko Alordiah
University of Delta, Agbor, Nigeria

Oyaziwo Omon Aluede
Ambrose Alli University, Ekpoma, Nigeria

ABSTRACT

The pervasive issue of academic dishonesty in higher education is exacerbated by evolving digital technologies. This study empirically investigates the relative and hierarchical predictive power of institutional, personal, social, and digital factors on the frequency of cheating behavior among university students. A cross-sectional survey design was employed with a sample of 1,120 students. Data were analyzed using bivariate correlations and a five-step hierarchical regression analysis. Rigorous diagnostic checks were conducted to validate the model. Bivariate correlations revealed significant relationships between all the predictors and cheating, with the digital factor showing the strongest association ($r = .570$). The final regression model explained 41.2% of the variance in cheating behavior. The digital factor is the most potent unique predictor ($\beta = .416, p < .001$), followed by peer pressure ($\beta = .132, p = .005$), social norms ($\beta = .108, p = .021$), and moral disengagement ($\beta = .096, p < .001$). The effect of the institutional factor is diminished but significant ($\beta = .074, p = .007$), whereas the effects of the lecturer-related factors and self-efficacy are nonsignificant. Academic cheating is a multifaceted phenomenon, but digital access emerges as the paramount facilitator. Interventions must adopt a holistic approach that simultaneously addresses technological, social, and institutional dimensions.

Keywords: Academic cheating, Digital technology, Neutralization**,** TPB, SAT

INTRODUCTION

The technologicalization of learning processes has led to a tremendous transformation and paradigm shift within the educational ecosystem. Adding to this change is the evolution of artificial intelligence (AI) tools that can address students' learning needs (Sampah et al., 2026; Lavidas et al., 2024). Its integration into learning environments has significantly affected higher education worldwide, even in Africa (Ndungu & Chepsergon, 2024). Many students use AI tools, such as ChatGPT, which has been found to be the most popular choice among Nigerian students. AI tools have enhanced creative and engaging learning (Aluko et al., 2025; Sağın et al., 2023) but have also made it possible for students to write academic papers without their personal inputs (Yavich & Davidovitch, 2024; Salinas-Navarro et al., 2024; Elkhatat, Elsaid & Almeer, 2023; Aravantinos et al., 2024; Liu et al., 2023; Zhai, Wibowo, & Li, 2024). Students' increasing dependence on AI technology poses challenges to academic integrity (Roe, Renandya & Jacobs, 2023). The presence of tools such as ChatGPT, Jasper, and QuillBot in the learning environment has increasingly raised urgent questions in terms of authorship, originality, and academic integrity among students in higher institutions (Guadu et al., 2026). Students often engage in cheating in academic settings to unfairly improve their exam scores (Anitha & Sundaram, 2022).

Many factors contribute to academic misconduct in Nigerian universities, including digital technology which is a major facilitator of modern cheating. Students' digital cheating in countries such as Nigeria is even more complicated as Shadare and Abubakar (2022) reported that Nigerian students' rapid adaptation to AI tools seems to have outdated institutional policies aimed at curbing academic misconduct. Thus, academic integrity, which refers to the ethical guidelines to promote trust and fair evaluations (Sefcik et al., 2020), has experienced major setbacks with the evolution and integration of AI as a learning tool. Even though tools such as Turnitin could enhance academic honesty, Sarwari and Mohd (2024) reported that the tool only helps students make efforts to pass plagiarism checks, without fostering creative and deep learning experiences. It is becoming increasingly worrisome as cheating continues to thrive in the academic environment. Corroborating this position, Dangiso et al. (2026) observed a permissive norm toward academic dishonesty, cutting across the demographic characteristics of students including gender and grade level.

LITERATURE REVIEW

Previous studies have confirmed the pervasiveness of digital tools as underlying factors of academic unethical conduct (Abubakar et al., 2024; Ukeje et al., 2024; Balogun, 2023; Adiyono et al., 2025; Hasanein & Sobaih, 2023, Izevbigie, 2025; Osang, Idiong & Akanimoh, 2025; Arowolo-Ayodeji, 2025; Sun et al., 2025; Benke & Szőke, 2024; Sun et al., 2025; Orok et al., 2024; Ndungu & Chepsergon, 2024; Ukeje et al., 2025; Sozon et al., 2024).

Apart from the digital technology path to academic dishonesty, academic pressure, peer influence, social norms, institutional support, self-efficacy, moral disengagement, and lecturer-related factors may play critical roles in enhancing academic cheating. Previous studies have confirmed the prevalence of these predictors in association with unethical academic practices among students. Yavich and Davidovitch (2024) reported that poor class attendance and low self-efficacy enhanced dishonest academic activities. Anitha et al. (2022) reported peer pressure and behavioral problems as banes of academic honesty. Sun et al. (2025) cited the personality and educational level of students as drivers of cheating. Marais (2022) cited a lack of institutional academic integrity codes as the root cause of academic fraud. Olawale and Ologunde (2022) reported institutional failure to check for AI abuse as the reason for academic misconduct.

Previous studies have also indicated that systemic corruption, institutional weaknesses, and students' pressure to achieve good grades (Ndungu & Chepsergon, 2024); a lack of consensus between teachers and students on the seriousness of cheating (Alcalde-Fradejas et al., 2024); and poor supervision and a lack of institutional administrative commitment (Mireku et al., 2024) are factors sustaining academic misconduct among students. Previous studies have equally associated moral disengagement with academic dishonesty (Heriyati & Ekasari, 2020; Chala, 2021; Rifani et al., 2021). In addition, some researchers have noted personal beliefs and values (Ismail & Omar, 2017), the failure of lecturers and institutions to combat the trend (Azemi et al., 2024), poor pay and a lack of motivational incentives (Olawole et al., 2025), and lecturers' complacency toward cheating (Mukasa et al., 2023) as reasons for the sustained incidents of academic fraud among students. Furthermore, in a single study, Eneji et al. (2022) confirmed fourteen (14) causes of academic dishonesty, cutting across institutional, personal, and corrupt practices and logistic problems among others.

A review of previous studies reveals the dangerous cheating trends that are ravaging academic integrity in the university education system across various backgrounds and cultures, indicating that cheating has become a global challenge.

Theoretical Framework

Academic dishonesty among students has been widely evaluated from different theoretical perspectives to account for the personal, social, and environmental determinants that influence students' cheating acts. In an attempt to add a voice to this trending and disturbing scholarship discourse on unethical academic practices among students, this study relies on three complementary theoretical lenses, namely, the theory of planned (TPB), neutralization theory, and situational action theory (SAT). The theory of planned behavior (TPB), as postulated by Ajzen (1991), contends that human behavior is guided by behavioral intentions, which are shaped by attitudes, subjective norms, and perceived behavioral control. Linking the TPB to cheating, it proposes that students practice academic dishonesty when they are favorably disposed to cheating attitudes, enjoy support from peers or social groups, and believe that they have the ability and opportunity to cheat without being caught.

Neutralization theory, proposed by Sykes and Matza (1957), posits that an individual can justify or rationalize deviant behavior to minimize feelings of guilt to maintain a positive self-image. This theory may provide a plausible explanation for why some students engage in cheating and do not see themselves as academically dishonest. Such students rely on neutralization techniques such as denial of responsibility ("I had no choice because the exam was difficult."), denial of injury ("I do not hurt anyone when I cheat."), condemnation of the condemners ("After all, my lecturers failed to teach well."), appeal to higher loyalties ("I only did it to assist a weak friend."), and denial of the victim ("I am not bad; after all, everyone does it.") to deactivate guilt triggers.

The situational action theory (SAT) proposed by Wikström (2004, 2010) argues that engagement in deviant acts is anchored to the interaction between an individual's moral tendencies and the immediate stimulating environment. Linking the theory to cheating contexts means that students with certain moral inclinations that align with cheating behavior cheat if they have the opportunity to do so when triggered by cheating environments, such as poor supervision and institutional failure to check for the unethical use of AI tools.

The integration of the TPB, neutralization theory, and SAT in this study provides a robust theoretical platform for evaluating the predictors of academic dishonesty. The TPB captures individual attitudes and social cheating influences; neutralization theory highlights the cognitive justifications of academic cheaters; while the SAT explains the environmental and situational triggers of academic dishonesty. These theories collectively guide the identification of personal, social, and contextual predictors of cheating among students.

Rationale of the Study

Unethical academic misconduct has become a social menace in higher institutions in many parts of the world. Tech advancement has equally added to the rising trends of cheating acts. This could be observed in the increasing AI-related cheating cases among students (Abubakar et al.,2024; Ukeje et al., 2024; Balogun, 2023; Adiyono et al., 2025; Hasanein & Sobaih, 2023, Izevbigie, 2025; Osang, Idiong & Akanimoh, 2025; Arowolo-Ayodeji, 2025; Sun et al., 2025; Benke & Szőke, 2024; Sun et al., 2025; Orok et al., 2024; Ndungu & Chepsergon, 2024; Ukeje et al., 2025; Sozon et al., 2024). The ease of accessing information through AI tools provides a platform for cheating to fester. This aligns with the proposition of planned behavior theory (TPB), which holds that individuals inclined to cheat are likely to engage in academic dishonesty when a favorable opportunity arises. Similarly, students rely on neutralization to minimize the implications of cheating, thereby increasing their likelihood of using digital technology to cheat. In addition, some students still take advantage of situations such as institutional lapses to address the unethical use of digital tools to cheat.

Thus, students' propensity to cheat (TPB), to rationalize (neutralization), and to take advantage of institutional failure (SAT) provide unique lenses for understanding cheating behavior in this study. Academic, social norms, institutional failure, moral disengagement, and lecturer-related factors, among others (Patnayakuni, et al., 2021; Ndungu, et al., 2024; Alcalde-Fradejas et al.,2024; Mireku et al., 2024; Eneji, et al., 2022; Ismail, et al., 2017; Azemi, et al., 2024; Olawole, Olugbemi, et al., 2025; Mukasa, et al., 2023), have been investigated as underlying causes of cheating, but the power of the digital factor as a potential strongest predictor among other predictors of cheating has been seldom examined. Other determinants may be dwarfed by digital factors, given that digital tools are becoming more available and may substantially change students' cheating trajectory. Thus, predictors of cheating, such as moral disengagement, peer influence and institutional failure, may be mediated in their relationship with cheating by the strongest predictor, possibly the digital factor. In other words, the digital factor may serve as the major pipeline or conduit linking other predictors to cheating.

Considering the impact of digital transformation in the modern educational setting, there is a strong likelihood of a major shift in the determinants of cheating, requiring a careful examination of cheating contexts to understand their current strengths. Thus, it is imperative to elucidate the status of these predictors with respect to students' unethical academic behaviors in this study. It is hoped that an understanding of these variables with a spotlight on digital factors may provide the empirical evidence that is needed by education actors to address cheating behavior among university students with more precision.

Hypotheses

H1: Digital factors will be the strongest positive predictor of cheating behavior.
H2: Social factors (peer pressure and social norms) are significant predictors.
H3: Institutional factors will have a significant but moderate positive relationship.
H4: Moral disengagement is a significant predictor.
H5: Lecturer-related factors and self-efficacy will have weak or nonsignificant effects.

METHODS

Research Design and Participants

Design

This study adopts a quantitative cross-sectional online survey design. This design is considered suitable for this study since the intention of the work is to investigate the hierarchy of the underlying factors of academic dishonesty among students. To determine the hierarchy of these variables in terms of their influence on academic dishonesty, this study presents findings concerning interactions among the frequency of cheating behavior, institutional factors, lecturer-related factors, self-efficacy, peer pressure, moral disengagement, social norms, social factors, and digital factors. This study is part of a larger study conducted on the underlying factors of academic dishonesty among university students in Nigeria.

Participants

The target population comprised undergraduate students enrolled in Nigerian universities. The participants (1,120) were between 16 and 31 years old. This was done in line with the minimum age requirement for enrollment into universities in Nigeria, which is 16 years. The participants were also students at the 100 to 600 level.

Measures

This study used a structured, self-administered questionnaire comprising validated scales developed by the researchers based on prior empirical studies. The instrument consists of nine domains, namely, cheating behavior frequency, institutional factors, lecturer-related factors, self-efficacy, peer pressure, moral disengagement, social norms, social factors, and digital factors. The test items include cheating behavior frequency (e.g., "I have cheated at least once in the past year."); institutional factors (e.g., "My university lacks strict anticheating policies."); lecturer-related factors (e.g., "Lecturers' poor teaching skills encourage cheating."); self-efficacy (e.g., "I am confident I can pass exams without cheating.”); peer influence (e.g., “I feel pressured to cheat to maintain friendships.”); moral disengagement (e.g., “Cheating is okay if the course is irrelevant to my career.”); social norms (e.g., “My peers approve of cheating to pass exams.”); social factors (e.g., “Family pressure to succeed pushes students to cheat.”); and digital factors (e.g., “I use smartphones to access answers during exams.”).

The instrument is composed of two sections: Section ‘A’ contains the biodata of the respondents. Section ‘B’ contained test items based on a 5-point rating scale: strongly agreed (5), agreed (4), neutral (3) disagreed (2) and strongly disagreed (1). The participants were asked to select only one option for each of the items available in the questionnaire. The instrument was validated by three experts in the field of education, including a measurement and evaluation expert. Reliability was established on the basis of the Cronbach’s alpha reliability method. The 9 domains of the instrument yielded the following Cronbach reliability coefficients: cheating behavior frequency (0.82), institutional factor (0.81), lecturer-related factor (0.82), self-efficacy (0.83), peer pressure (0.81), moral disengagement**,** social norms (0.80), social factor (0.83), and digital factor (0.82).

Data collection procedures

Data were collected electronically through online Google Forms. The researchers randomly sent the Google Forms links to many students and group platforms and sought their consent to participate in the study. Instructions concerning how to complete the form were adequately explained to the respondents. The researchers ensured the anonymity of the respondents. Students within the target population willingly participated in the survey and were free to withdraw at any stage. The participants completed Section A, biodata before proceeding to Section B to respond to the test items. After the survey was completed, the participants pressed the ‘Submit’ button on the Google Forms to send their feedback to the research database electronically. The survey lasted for approximately four weeks.

Ethical Considerations

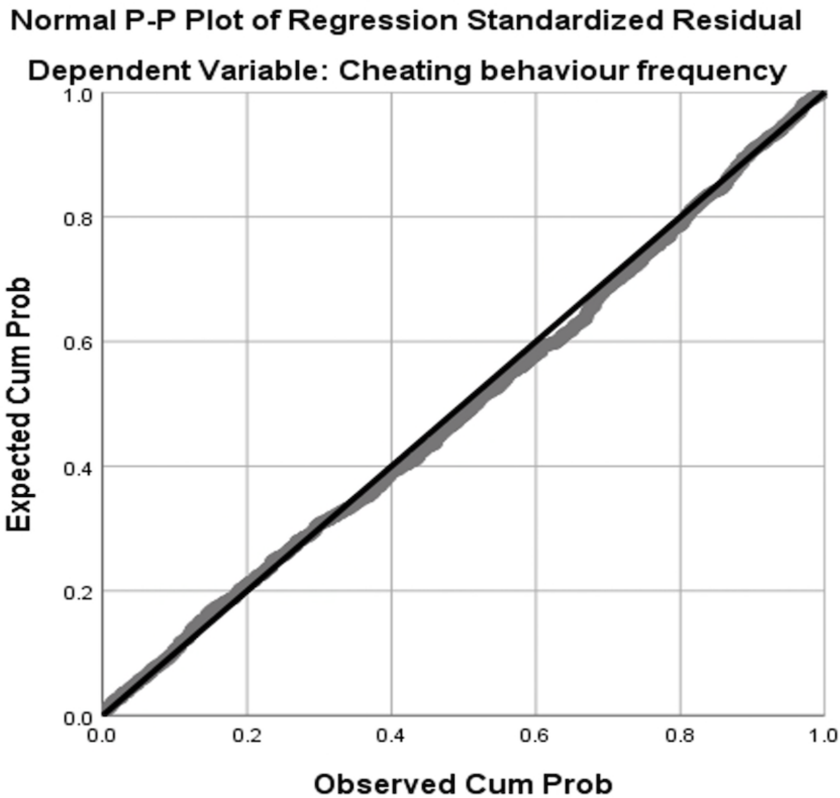
Full ethical approval for the research was obtained from Ambrose Alli University, Ekpoma, Nigeria, Health Research Ethical Committee, which is a registered committee with the registration number NHREC/12/06/2013. The Health Committee’s assigned number for this research is **220/25**. In addition, informed consent was obtained from all participants. Participation was voluntary, as the participants were given the right to withdraw at any time or at any stage of the survey. The questionnaires were completed anonymously.

Data Analysis

Preliminary analysis involved descriptive statistics and bivariate correlations. The main analysis was a hierarchical multiple regression with variables entered in five blocks. Diagnostic checks confirmed that all assumptions of multiple regression were met: normality (Figure 1), linearity and homoscedasticity (Figure 2), and the absence of multicollinearity (Table 5). The residual statistics (Table 5) confirmed that there were no influential outliers.

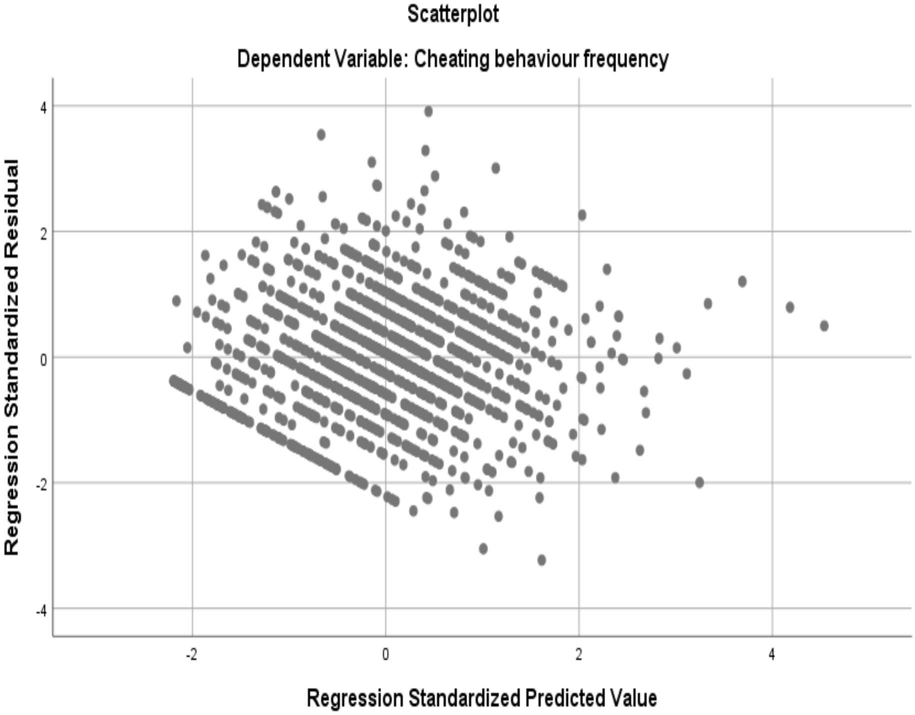
Figure 1: *Normal Probability–Probability (P–P) Plot of Standardized Residuals Evaluating the Normality Assumption for the Cheating Behavior Model*

Assumption Diagnostics



The normal P–P plot of the standardized residuals is shown in Figure 1. The points lie close to the diagonal line, indicating that the residuals follow a nearly perfect normal distribution. Only minor deviations appear at the extremes. This confirms that the regression model satisfies the normality assumption, supporting the validity, reliability, and accuracy of the model's predictions.

Figure 2: *Scatterplot of Standardized Predicted Values Against Standardized Residuals Assessing Linearity and Homoscedasticity in the Regression Model*



A scatterplot of the standardized residuals against the standardized predicted values is shown in Figure 2. The points appear randomly scattered with no clear pattern, curve, or funnel shape. This finding indicates that the assumptions of linearity and homoscedasticity are met. The spread of residuals is fairly consistent across the predicted values, suggesting that the regression model fits the data appropriately without systematic bias.

RESULTS

This section presents the findings from the correlational and inferential analyses conducted to examine the factors predicting the frequency of cheating behavior among students. The analysis progressed from descriptive summaries to correlation patterns and, finally, to stepwise multiple regression. Additional diagnostic checks were performed to assess model adequacy and compliance with statistical assumptions.

Descriptive statistics and bivariate correlations

Table 1: Correlation Matrix for the Cheating Behavior Frequency and Predictor Variables

Variable	1	2	3	4	5	6	7	8	9
1. Cheating Behavior Freq.	—								
2. Institutional Factor	.363*	—							
3.Lecturer-Related Factor	.135*	.221*	—						
4. Self-Efficacy	.118*	.274*	.166*	—					
5. Peer Pressure	.453*	.326*	.053*	-.043	—				
6.Moral Disengagement	.302*	.260*	.075*	-184*	.451*	—			
7. Social Norms	.462*	.371*	.078*	-.030	.863*	.447*	—		
8. Social Factor	.235*	.314*	.427*	.160*	.241*	.188*	.222*	—	
9. Digital Factor	.570*	.396*	.184*	.212*	.378*	.195*	.400*	.266*	—

Note: N = 1120 for all correlations. $p < .05$.

A correlation matrix was computed to assess the relationships between the frequency of cheating behavior and the eight predictor variables (Table 1). All the predictors demonstrated statistically significant positive correlations with cheating behavior (p < .05). The digital factor exhibited the strongest bivariate correlation (*r* = .570), followed by social norms (*r* = .462) and peer pressure (*r* = .453). institutional factor (*r* = .363) and moral disengagement (*r* = .302) showed moderate correlations, whereas lecturer-related factor (*r* = .135) and self-efficacy (*r* = .118) demonstrated weaker, although significant, relationships. A notably high correlation was observed between peer pressure and social norms (*r* = .863), suggesting substantial overlap between these two social constructs.

Hierarchical Regression Analysis

Table 2: Summary of Hierarchical Regression Models for Variables Predicting Cheating Behavior Frequency

Model	Predictors	R	R^2	Adj. R^2	ΔR^2	Sig. F Change
1	Institutional Factor	.363	.132	.131	—	.000
2	+ Lecturer-Related Factor	.367	.135	.134	.003	.043
3	+ Self-Efficacy, Peer Pressure	.515	.266	.263	.131	.000
4	+Social Factor, Moral Disengagement, Social Norms	.534	.286	.281	.020	.000
5	+ Digital Factor	.642	.412	.408	.126	.000

Note: Dependent Variable: Cheating behavior frequency.

Table 3: ANOVA Results for Hierarchical Regression Models

Model	Sum of Squares	Df	Mean Square	F	Sig.	
1	Regression	2365.32	1	2365.32	169.84	.000
	Residual	15569.93	1118	13.93		
	Total	17935.25	1119			
2	Regression	2422.20	2	1211.10	87.20	.000
	Residual	15513.05	1117	13.89		
	Total	17935.25	1119			
3	Regression	4765.91	4	1191.48	100.88	.000
	Residual	13169.35	1115	11.81		
	Total	17935.25	1119			
4	Regression	5123.90	7	731.99	63.54	.000
	Residual	12811.35	1112	11.52		
	Total	17935.25	1119			
5	Regression	7389.77	8	923.72	97.32	.000
	Residual	10545.48	1111	9.49		
	Total	17935.25	1119			

Hierarchical multiple regression was conducted to examine the unique contribution of various blocks of predictors to the variance in the frequency of cheating behavior. The results of the model summary and ANOVA are presented in Tables 2 and 3, respectively. Model 1, which included only the institutional factor, was statistically significant and accounted for 13.2% of the variance in cheating behavior ($R^2 = .132$, $F(1, 1118) = 169.84$, $p < .001$). The addition of the lecturer-related factor in Model 2 led to a very small but significant increase in explained variance ($\Delta R^2 = .003$, $p = .043$), with the model explaining 13.5% of the variance ($F(2, 1117) = 87.20$, $p < .001$). Model 3 introduced self-efficacy and peer pressure, resulting in a substantial increase in explanatory power. This model explained 26.6% of the variance, representing a significant R^2 change of .131 ($F(4, 1115) = 100.88$, $p < .001$). The inclusion of social factor, moral disengagement, and social norms in Model 4 further increased the explained variance to 28.6% ($\Delta R^2 = .020$, $F(7, 1112) = 63.54$, $p < .001$). The final model (Model 5), which included the digital factor, explained 41.2% of the variance in the frequency of cheating behavior. The addition of this variable resulted in a large and significant increase of 12.6% in explained variance ($\Delta R^2 = .126$, $F(8, 1111) = 97.32$, $p < .001$). The ANOVA results confirmed that each successive model was statistically significant ($p < .001$).

Table 4: Regression Coefficients for Hierarchical Models Predicting Cheating Behavior Frequency

Model & Predictor	B	SE B	Β	T	P
Model 1					
(Constant)	7.208	.370		19.459	<.001
Institutional Factor	.408	.031	.363	13.032	<.001
Model 2					
(Constant)	6.434	.532		12.095	<.001
Institutional Factor	.393	.032	.350	12.281	<.001
Lecturer-Related Factor	.053	.026	.058	2.024	.043
Model 3					
(Constant)	3.494	.635		5.503	<.001
Institutional Factor	.231	.032	.206	7.111	<.001
Lecturer-Related Factor	.054	.025	.058	2.192	.029
Self-Efficacy	.059	.023	.068	2.511	.012
Peer Pressure	.653	.046	.386	14.078	<.001
Model 4					
(Constant)	2.536	.668		3.798	<.001
Institutional Factor	.178	.034	.159	5.320	<.001
Lecturer-Related Factor	.028	.026	.030	1.074	.283
Self-Efficacy	.080	.024	.092	3.327	.001
Peer Pressure	.307	.086	.182	3.562	<.001
Moral Disengagement	.104	.032	.098	3.288	.001
Social Norms	.316	.085	.192	3.731	<.001
Social Factor	.049	.028	.053	1.780	.075
Model 5					
(Constant)	1.849	.608		3.042	.002
Institutional Factor	.084	.031	.074	2.690	.007
Lecturer-Related Factor	.006	.024	.006	0.238	.812
Self-Efficacy	.027	.022	.032	1.245	.214
Peer Pressure	.223	.079	.132	2.838	.005
Moral Disengagement	.102	.029	.096	3.541	<.001
Social Norms	.178	.077	.108	2.303	.021
Social Factor	.018	.025	.020	0.727	.468
Digital Factor	.404	.026	.416	15.450	<.001

Note: Dependent Variable: Cheating behavior frequency.

The regression coefficients for each model are presented in Table 4. In the final model (Model 5), the digital factor was the strongest unique predictor ($\beta = .416$, $p < .001$). Peer pressure ($\beta = .132$, $p = .005$), social norms ($\beta = .108$, $p = .021$), and moral disengagement ($\beta = .096$, $p < .001$) also emerged as significant positive predictors. The institutional factor remained a significant, although weaker, predictor ($\beta = .074$, $p = .007$). Lecturer-related factors ($\beta = .006$, $p = .812$), self-efficacy ($\beta = .032$, $p = .214$), and social factors ($\beta = .020$, $p = .468$) were not significant in the final model.

Table 5: Collinearity and Residual Diagnostics for the Final Regression Model (Model 5)

Diagnostic	Statistic	Value	Interpretation
Collinearity Statistics (Tolerance)	Institutional Factor	.730	Acceptable (> 0.10)
	Lecturer-Related Factor	.744	Acceptable (> 0.10)
	Self-Efficacy	.744	Acceptable (> 0.10)
	Peer Pressure	.246	Acceptable (> 0.10)
	Moral Disengagement	.735	Acceptable (> 0.10)
	Social Norms	.246	Acceptable (> 0.10)
	Social Factor	.740	Acceptable (> 0.10)
	Digital Factor	.730	Acceptable (> 0.10)
Residuals Statistics	Std. Residual Min	-3.232	Within acceptable range
	Std. Residual Max	3.912	Within acceptable range
	Mean of Std. Residuals	.000	As expected
	Std. Deviation of Residuals	.996	As expected

Note: N = 1120. Dependent Variable: Cheating behavior frequency.

The diagnostic checks performed on the final regression model confirmed its robustness and validity. As presented in Table 5, the collinearity statistics revealed that all the tolerance values were within acceptable limits, indicating that multicollinearity did not bias the regression coefficients. Additionally, the analysis of standardized residuals revealed a mean of zero and a standard deviation of one, with no extreme outliers, indicating that the model's errors were normally distributed and that the results were not unduly influenced by individual data points.

DISCUSSION AND CONCLUSIONS

The findings of this study reveal the paramount role of the digital factor in relation to academic misconduct. This confirms H1, as digital technology is a fundamental enabler of cheating in this study. The outcome of this study may be associated with the complementary roles of planned behavior or inclinations to cheat and peer approval to do so (Ajzen.1991), justification of cheating through neutralization (Sykes, et al., 1957), and cheating environments made available through institutional failure to combat cheating (Wikström; 2004, 2010). These findings also agree with those of Roe et al. (2023) who reported that students' overreliance on AI tools poses challenges to academic integrity.

Previous studies have confirmed the pervasiveness of digital tools as underlying factors of unethical conduct. Thus, these results resonate with those of previous studies that reported digital tools as enablers of academic cheating (Abubakar et al., 2024; Ukeje et al., 2024; Balogun, 2023; Adiyono et al., 2025; Hasanein & Sobaih, 2023, Izevbigie, 2025; Osang et al., 2025; Arowolo-Ayodeji, 2025; Sun et al., 2025; Benke & Szőke, 2024; Sun et al., 2025; Orok et al., 2024; Ndungu, et al., 2024; Ukeje et al., 2025; Sozon et al., 2024). It also confirms that the increasing popularity of AI use among students has negative effects on academic honesty. These findings further prove that university students in Nigeria are catching up with trending digital cheating similar to their peers in other parts of the world. The results reveal that the digital factor is the most potent determinant of cheating, underscoring the importance of a new approach to address cheating in universities in Nigeria and beyond. Institutional interventions should target an adequate orientation on the proper use of AI tools to help students differentiate between ethical and unethical technological use in academic activities.

This study also reveals a powerful social ecosystem with the intertwined role of peers and social norms in enabling academic misconduct. These findings confirm H2, as peer influence and social norms are significant enablers of cheating. The results of this study could be the consequence of the intertwined implications of the TPB (Ajzen.1991), neutralization theory (Sykes, et al., 1957), and SAT (Wikström; 2004, 2010). Many students who are inclined to engage in unethical behavior are very likely to cheat when they realize that they will also enjoy peer approval and coverage. Peer influence and procheating social norms can further strengthen cheaters' ability to take advantage of poor lecturers' supervision and other institutional lapses to cheat and justify actions through neutralization processes. Peer influence plays a critical role in students' behavior because it determines peer expectations and serves as a standard for social integration among peer group members. Those who flout peer cheating norms may face social rejection or stigmatization and are labeled weak and unsociable or untrendy.

This study also aligns with previous studies that confirmed peer influence and social norms as predictors of academic dishonesty (Sozon et al., 2024; Thomas, 2020; Anitha, et al., 2022; Ndungu, et al., 2024; Eneji, et al., 2022). Having observed the strength of peers and social norms in this study, it becomes necessary that university institutions in Nigeria and beyond should prioritize addressing peer influences and social norms that are inherent to academic integrity headlong. School counsellors play critical roles through their statutory information services to educate students on the need to shun peer pressures or norms that oppose academic integrity. The findings of this study also prove that peer pressure as a predictor of cheating is a universal phenomenon as confirmed by similar studies reviewed from diverse sociocultural backgrounds in this study. Interventions should target peer pressure indicators that are inimical to academic honesty through appropriate institutional policies.

The results of this study reveal institutional contexts as foundational to cheating and as a mediating path to dishonest academic acts. These results partially confirm H3, as institutional contexts are significant, although weaker predictors in the interplay ($\beta = .074$, $p = .007$). The results of this study may provide evidence that unethical tendencies are intensified through weak institutionalized structures that are incapable of stemming the tide of cheating. Previous studies have reported institutional factors as enablers of cheating (Marais, 2022; Ndungu et al., 2024;

Mireku et al., 2024; Eneji, et al., 2022; Azemi, et al., 2024). However, this study reveals that institutional factors, in addition to being enablers, provide a buffer for other factors to thrive. For instance, students may have the tendency to cheat and may desperately look for opportunities to do so but can be blocked from achieving such goals through effective institutional anticheating strategies. On the other hand, weak institutional policies on cheating could provide a launch pad for desperate students to cheat, thereby serving as a conduit for the facilitation of digital technology and social norm actors to thrive in the cheating chain.

The results also reveal the role of students' internal justification in enhancing academic dishonesty. These findings confirm H4, as moral disengagement significantly predicted cheating. These findings reveal the importance of the moral compass which could enhance academic integrity. This means that the higher the moral standards of students are, the greater the likelihood that they will not cheat. On the other hand, moral disengagement can cause a strong pull on students to cheat when they have deactivated their moral compass by neutralizing the implications of cheating. This aligns with Sykes et al.'s (1957) neutralization theory, which proposed that the neutralization of deviant behavior to maintain a positive image could drive individuals to engage in unethical behavior.

Moral disengagement can be strengthened by social norms, peer pressure and unlimited access to digital technology. Previous studies have confirmed that moral disengagement is related to academic dishonesty (Heriyati, et al., 2020; Chala, 2021; Rifani, et al., 2021). Intervention strategies should involve the institutional rebirth of moral integrity through the incentivization and enforcement of disciplinary codes. Students who exhibit good and exemplary behavior should be rewarded and used for integrity advocacy campaigns on campuses. Institutions should also enforce their conduct codes for established cases of academic misconduct. Institutional failure and corrupt practices of lecturers during examination supervision should be dealt with to serve as deterrents and raise academic integrity bars across university institutions. Academic integrity should be perceived as a community value, which requires full participation and cooperation from all members of the community to ensure its survival (Hurley et al., 2026).

This study reveals the diminished role of lecturers and self-efficacy as they were overshadowed by stronger drivers. These results confirm H5, as the lecturer-related factor ($\beta = .006$, $p = .812$) and self-efficacy ($\beta = .032$, $p = .214$) are not significant predictors. Previous studies have revealed that lecturer-related factors (Ismail, et al., 2017; Azemi, et al., 2024; Olawole, et al., 2025; Mukasa et al., 2023) and self-efficacy-related factors (Yavich, et al., 2024; Anitha, et al., 2022; Sun et al., 2025) are underlying causes of academic dishonesty. However, in this study, the results reveal the dwindling power of both lecturer-related and self-efficacy factors. The reason for this contextual change may be attributable to the presence of stronger drivers of cheating which have dwarfed their effects in their interactions with academic dishonesty. For instance, digital factors can overshadow self-efficacy factors because digitalization facilitates cheating with ease. This means that students who are academically capable may still engage in digital cheating because it makes it easy for them to complete academic tasks in time. Similarly, intelligent students may still indulge in digital cheating to blend with peers who have normalized cheating.

Lecturer-related factors are also overshadowed most likely because modern university students rely more on AI for personalized learning. Thus, the line between cheating and lecturer-related factors may be blurred by digital technology, peer influence and social norms. However, the role of lecturer-related and self-efficacy factors as drivers of academic dishonesty should be trivialized, as they can serve as buffers to other cheating predictors. Lecturers' leniency in detecting plagiarism could bolster digital cheating. In the same vein, self-efficacy could be channeled into digital cheating adventures by intelligent students because using digital tools to cheat requires digital literacy; hence, digital literacy may be a subtle motivation for students with high self-efficacy to explore cheating to earn high grades with ease. Therefore, institutions of higher learning should still address both lecturer-related and self-efficacy factors even though they are weak predictors of cheating in this study.

Limitations and Suggestions for Future Research

This study has several limitations. It is a cross-sectional survey that could not penetrate deeply since the respondents were not studied for a long time. Furthermore, the analyses are based on self-reported data from students. Respondents are prone to align with certain responses that they may consider 'suitable' on the basis of peer influence and social norms. Again, cultural contexts may reflect the tone of the findings of this study. Thus, similar research should be carried out in other regions for comparative purposes. Qualitative and longitudinal studies may also help to deepen research penetration.

IMPLICATIONS

The findings of this study have practical implications for various academic integrity drivers to address academic dishonesty. There are several implications for university institutions. Institutions of higher learning need to perform holistic assessments of digital technology and AI integration in learning processes. These assessments should lead to the redesign and reimaging of academic integrity codes with clear definitions of what constitutes academic dishonesty with new policies that can address modern cheating contexts. Institutions also need to engage other stakeholders to arrive at policies or decisions that are in tandem with the principles of equity and inclusivity. For instance, students should be involved in the process of fashioning out strategies to curb cheating.

Similarly, there are implications for lecturers. They should adopt new approaches to combat cheating among students. Ensuring that students are taught and given sufficient support is paramount. Lecturers should look inward to ensure that they maintain high professional standards to foster a culture of integrity. Corrupt practices linked to aiding and abetting cheating should be thoroughly investigated and appropriately sanctioned if cases are established to serve as deterrents.

In addition, there are implications for university counsellors. Counsellors should make good use of students' orientation programs to engage students with talks related to academic integrity. They should also engage students who indulge in cheating behaviors with appropriate interventions to help them regain their moral compass.

CONCLUSION

Cheating is a complex syndrome driven most powerfully by digital technology within permissive social and institutional contexts. The increasing use of AI tools has continued to leverage cheating instances among university students, making digital cheating the most prominent source of academic misconduct in recent years. The present study has investigated how the rising threat of digital tools can infiltrate academic practices in higher institutions of learning if pro-academic-integrity actors do not take drastic action. Peer influence, social norms and moral disengagement are significant paths to unethical academic conduct but can be dwarfed by digital technology, which has proven to be the strongest channel of academic misconduct in this study.

Lecturer-related and self-efficacy factors are weak routes to cheating contexts among Nigerian university students, as evidenced in this study, because the combination of digital technology, peer influence, and social norm pathways limited their effects. This suggests that dealing with cheating requires multipronged and systematic interventions since the interplay of cheating contexts is becoming more complex, especially with the integration of digital technology, particularly AI, in the educational ecosystem. Academic and cultural factors can motivate students to study (Sozon et al., 2024; Thomas, 2020) and minimize cheating tendencies. Thus, institutional culture should tilt toward promoting ethical practices and restoring moral conduct on campuses.

As observed by Rivas-Aceves and Ortega-Barba (2026) appropriate interventions could foster a greater inclination to reject academic fraud. AI literacy initiatives could also foster responsible engagement with digital technologies (Prime et al., 2026) and help minimize digital cheating emanating from ignorance of ethical use boundaries. Thus, institutions should increase the likelihood of de-escalating cheating among university students through clear rules, digital literacy, and the consistent enforcement of institutional frameworks that are goal-driven.

DECLARATIONS

Ethics approval and consent to participate
Ethical approval was obtained for the study, and consent was obtained from all the students who participated.

Conflict of interest statement
The authors report that they have no conflicts of interest.

Funding
The study received no funding.

REFERENCES

Abubakar, U., Falade, A. A., & Ibrahim, H. A. (2024). Redefining student assessment in Nigerian tertiary institutions: The impact of AI technologies on academic performance and developing counter measures, *Advances in Mobile Learning Educational Research*, *4*(2), 1149-1159. https://doi.org/10.25082/AMLER.2024.02.009

Adiyono, A., Suwartono, T., Nurhayati, S., Dalimarta, F. F., & Wijayanti, O. (2025). Impact of artificial intelligence on student reliance for exam answers: A case study in IRCT Indonesia. *International Journal of Learning, Teaching and Educational Research*, *24*(3), 519–544. https://doi.org/10.26803/ijlter.24.3.22

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Anitha, P., & Sundaram, S. (2022). Experimental investigation of cheating behavior and qualitative analysis of antecedents of academic dishonesty among school students, *Journal of Positive School Psychology*, *6*(6), 2506-2515

Alcalde-Fradejas N, Marzo-Navarro M and Ramírez-Alesón M (2024) Faculty versus students: Different perceptions of misconducts at university. *Front. Psychol.* 15:1348057. doi: 10.3389/fpsyg.2024.1348057

Aluko, H., Offiah, G., Aluko, A., Ogunjimi, F., Aluko, A., Alalade, F., Ukeje, I.O, Nwani, C. (2025). Exploring the effectiveness of AI-generated learning materials in facilitating active learning strategies and knowledge retention in higher education. *International Journal of Organizational Analysis*. http://dx.doi.org/10.1108/IJOA-07-2024-4632

Aravantinos, S., Lavidas, K., Voulgari, I., Papadakis, S., Karalis, T., & Komis, V. (2024). Educational approaches with ai in primary school settings: A systematic review of the literature available in Scopus. *Education Sciences*, *14*(7), 744. https://doi.org/10.3390/educsci14070744

Arowolo-Ayodeji, A. (2025). The Role of AI and blockchain in combating academic fraud World, *Journal of Advanced Research and Reviews*, *25*(02), 1341-1357

Azemi, A., Azhar, S.M.F. & Jamaludin, N.A. (2024). Academic dishonesty in higher education: A bibliometric analysis. *International Journal of Religion, 5*(7), 1094 – 1103

Balogun, O. (2023). The role of AI in academic integrity: Challenges and solutions in the Nigerian context. *Journal of African Educational Technology*, *19*(2), 45-60.

Benke E., & Szőke A. (2024). academic integrity in the time of artificial intelligence: exploring student attitudes, *Italian Journal of Sociology of Education*, *16*(2), 91-108.DOI: 10.14658/PUPJ-IJSE-2024-2-5

Chala, W.D. (2021). Perceived seriousness of academic cheating behaviors among undergraduate students: an Ethiopian experience. *International Journal for Educational Integrity, 17*(2) https://doi.org/10.1007/s40979-020-00069-z

Dangiso M.S., Wontamo A.P. & Abera, B.B. (2026). Analysis of academic dishonesty among secondary school students with particular emphasis on attitudes, academic achievement, grade level and gender. *Discov Educ*. https://doi. org/10.1007/s44217-026-01429-6

Elkhatat, A. M., Elsaid, K., & Almeer, S. (2023). Evaluating the efficacy of AI content detection tools in differentiating between human and AI-generated text. *International Journal for Educational Integrity*, *19*(1). https://doi.org/10.1007/s40979-023-00140-5

Eneji, C.O., Petters,J.S., Stella Bassey Esuabana ,S.B., Onnoghen, N.U., Udumo, B.O., Ambe, B.A., Gregory, J.L. 2020. COVID-19 elevating the problem of plagiarism: the implied social contract of academic integrity. *Delta Kappa Gamma Bulletin*, *87*(1): 18-23.

Guadu, A., Dibekulu, D., & Walle Menberu, A. W. (2026). Academic integrity in the age of AI: challenges and strategies for African higher education. *Discover Education 5*, 21 https://doi.org/10.1007/s44217-025-01031-2

Heriyati, D., & Ekasari, W. F. (2020). A Study on academic dishonesty and moral reasoning, *Indonesian Journal of Education*, 12(2), 56-62. doi: 10.17509/ije.v12i2.18653.

Hurley, M., Casey, D., Morari, V., & Grimes, D. (2026). Where to from here? On the borders of academic integrity, academic misconduct, and assessment security after GenAI, Studies in Higher Education, DOI: 10.1080/03075079.2026.2614988

Izevbigie, H.I., Olajide, O., Olaniran, O. & Akintayo, T.A. (2025). The ethical use of generative AI in the Nigerian higher education sector, *World Journal of Advanced Research and Reviews*, *25*(03), 847-853

Lavidas, K., Voulgari, I., Papadakis, S., Athanassopoulos, S., Anastasiou, A., Filippidi, A., Komis, V., & Karacapilidis, N. (2024). Determinants of humanities and social sciences students' intentions to use artificial intelligence applications for academic purposes. *Information*, *15*(6), 314. https://doi.org/10.3390/info15060314

Liu, H., Azam, M., Bin., S., & Faiola, A. (2023). An overview of the capabilities of ChatGPT for medical writing and its implications for academic integrity. *Health Information and Libraries Journal*, *40*(4), 440–446. https://doi.org/10.1111/ hir.12509

Marais, I.E., (2022). Institutionalization of academic integrity: Experiences at a distance education university in South Africa during COVID-19. *Cristal*, *10,* 2 DOI: 10.14426/cristal. v10i2.585

Mireku, D. O., Dzamesi, P. D., & Bervell, B. (2024). plagiarism in higher education (PLAGiHE) within Sub-Saharan Africa: A systematic review of a decade (2012–2022) literature, *Research Ethics, 20*(2), 156-186

Mukasa, J., Stokes, L., & Mukona, D. M. (2023). Academic dishonesty among students of bioethics at a tertiary institution in Australia: An exploratory study. *International Journal for Educational Integrity*, *19*(1), 1-15.

Hasanein, A. M., & Sobaih, A. E. E. (2023). Drivers and consequences of ChatGPT use in higher education: Key stakeholder perspectives. *European journal of investigation in health, psychology and education*, *13*(11), 2599-2614. https://doi.org/ 10.3390/ejihpe13110181

Ndungu, N.J. & Chepsergon, K. A. (2024). Dual role of AI in academic dishonesty and integrity management in the institutions of higher learning in Sub-Saharan Africa, *Journal of Research in Education and Technology*, *2*(1) 69-79

Olawale, M., & Ologunde, O. (2022). Ghostwriting in the age of AI: Ethical concerns for Nigerian higher education. *Journal of African Educational Policy*, *27*(1), 58-72.

Olawole, A. O., Olugbemi, O., Ayodele, O. J. (2025). An investigation of academic dishonesty among undergraduate students in Federal University, Oye -Ekiti, Nigeria. *Unizik Journal of Educational Research and Policy Studies,19* (1), 268-276

Orok E, Okaramee C, Egboro B, Egbochukwu E, Bello K, Etukudo S, Ogologo MS, Onyeka P, Etukokwu O, Kolawole M, Orire A, Ekada I, Akawa O. (2024). Pharmacy students' perception and knowledge of chat-based artificial intelligence tools at a Nigerian University. *BMC Med Educ*,

31,24(1), 1237. doi: 10.1186/s12909-024-06255-8. PMID: 39482671; PMCID: PMC11526711.
Osang, O. G., Idiong, S.P., & Akanimoh, M.E. (2025). Unethical issues in the use of artificial intelligence (AI) among undergraduates in public universities of Cross River State, *Nigeria Journal of Humanities and Social Policy*, *11*(5), 136-146
Prime, G., Threadgill, B., Momoh, V., Anderson, P.C., Gole, R., Sharma, S., Mandal, U., Rajput, M., Garbuja, S., Tiwari, K., & Pandey, V. (2026). Understanding AI literacy among college students: Voices from a historically black college and university. *Journal of Interdisciplinary Studies in Education, 15* (2), 169-194 https://ojed.org/jise https://doi.org/10.32674/w76bnk04
Rifani, E., Sugiyo, S., & Purwanto, E. (2021). The mediation effect of moral disengagement on spiritual- religious attitudes and academic dishonesty among guidance and counseling students. *Islamic Guidance and Counseling Journal, 4*(1). https://doi.org/10.25217/igcj.v4i1.1147 E-ISSN: 2614-1566
Rivas-Aceves, S. & Ortega-Barba, C. F. (2026). Predictive factors of academic integrity in business students: A quantitative analysis. *Journal of Culture and Values in Education*, *9*(1), 86-105.https://doi.org/10.46303/jcve.2026.4
Roe, J., Renandya, W. A., & Jacobs, G. M. (2023). A review of AI-powered writing tools and their implications for academic integrity in the language classroom. *Journal of English and Applied Linguistics*, *2*(1). https://doi.org/10.59588/2961-3094.1035
Sağın, F. G., Özkaya, A. B., Tengiz, F., Geyik, Ö. G., & Geyik, C. (2023). Current evaluation and recommendations for the use of artificial intelligence tools in education. *Türk Biyokimya Dergisi*, *48*(6), 620–625. https://doi.org/10.1515/tjb-2023-0254
Salinas-Navarro, D. E., Vilalta-Perdomo, E., Michel-Villarreal, R., & Montesinos, L. (2024). Using Generative Artificial Intelligence Tools to Explain and Enhance Experiential Learning for Authentic Assessment. *Education Sciences*, *14*(1), 83. https://doi.org/10.3390/educsci14010083
Sampah, S.N.A., Nabang, M., Krampa, E.F., Issah, M., Koduah, F., Essel,H.B., & Agyem, J.A. (2026). Generative AI competence and student engagement in higher education: mediating roles of utilization, autonomy, and formal learning. *Journal of Interdisciplinary Studies in Education, 15* (2), 109-146 https://ojed.org/jise https://doi.org/10.32674/w76bnk04
Sarwari, A. Q., & Mohd, A. H. (2024). The effectiveness of artificial intelligence (AI) on daily educational activities of undergraduates in a modern and diversified university environment. *Advances in Mobile Learning*

Educational Research, *4*(1), 927–930. https://doi.org/10.25082/amler.2024.01.004

Sefcik, L., Striepe, M., & Yorke, J. (2019). Mapping the landscape of academic integrity education programs: what approaches are effective? *Assessment & Evaluation in Higher Education*, *45*(1), 30–43. https://doi.org/10.1080/02602938.2019.1604942

Shadare, A., & Abubakar, M. (2022). Student adoption of AI technologies: Implications for academic integrity in Nigerian universities. *Journal of Nigerian Studies in Education*, *31*(1), 95-110.

Sozon, M., Mohammad Alkharabsheh O.H., Fong, P.W.& Chuan, S.B. (2024). Cheating and plagiarism in higher education institutions (HEIs): A literature review F1000, *Research*, *13,*788 https://doi.org/10.12688/f1000research.147140.2

Sun, R., Tang, M., Zhou, J., Loan, N.T.T. & Wang, C.Y. (2025) The dark tetrad as associated factors in generative AI academic misconduct: insights beyond personal attribute variables. *Front. Educ. 10,* 1551721. doi: 10.3389/feduc.2025.1551721

Sykes, G. M., & Matza, D. (1957). Techniques of neutralization: A theory of delinquency. *American Sociological Review*, *22*(6), 664–670.

Thomas, D. (2020). Academic dishonesty, religious fundamentalism, among students at a religious university, *International Forum Journal*, *23*(1): 126–138.

Ukeje, I. O., Elom, C. O., Ayanwale, M. A., Umoke, C. C., & Nwangbo, S. O. (2025). Exploring an innovative educational governance framework: Leveraging artificial intelligence in a stakeholder-driven “open campus model” in South East Nigerian universities. *International Journal of Learning, Teaching and Educational Research*, *23*(6), 416–440. https://doi.org/10.26803/ijlter.23.6.19

Wikström, P. O. H. (2004). Crime as alternative: Towards a cross-level situational action theory of crime causation. In J. McCord (Ed.), *Beyond empiricism: Institutions and intentions in the study of crime* (pp. 1–37). Transaction.

Wikström, P. O. H. (2010). Explaining crime as moral actions. In S. Hitlin & S. Vaisey (Eds.), *Handbook of the sociology of morality* (pp. 211–239). Springer.

Yavich, R.; Davidovitch, N. (2024). Plagiarism among higher education students. *Educ. Sci*, *14*, 908. https://doi.org/10.3390/ educsci14080908

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of overreliance on AI dialog systems on students’ cognitive abilities: a systematic review. *Smart Learning Environments*, *11*(1). https://doi.org/10.1186/s40561-024-00316-7

Abel Enokela, Ph.D (Corresponding Author) is a senior lecturer in the Department of Educational Foundations, Federal College of Education, Ofeme-Ohuhu, Nigeria. His research interests focus on students' mental health, digital education, school adjustment, and academic integrity. Email:abelenokela2020@gmail.com, ORCID: 0000-0003-4488-8614

Caroline Alordiah, Ph. D is a senior lecturer in the Department of Educational Foundations, University of Delta, Agbor, Nigeria. Her research interests focus on academic measurement and evaluation and academic integrity.
Email: caroline.alordiah@unidel.edu.ng, ORCID: 0000-0002-2917-9302

Oyaziwo Aluede, Ph. D is a professor of Guidance and Counseling, Ambrose Alli University, Ekpoma, Nigeria. His research interests focus on students' mental health, school counseling, and academic integrity.
Email: oyaziwoaluede@aauekpoma.edu.ng, ORCID: 0000-0003-1667-9954