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Integrating Artificial Intelligence in Emotional Intelligence, Self-Awareness and Mental Health in Educational Settings in Nigeria

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Abstract

The teaching of English Language in tertiary institutions has continued to face challenges due to overdependence on traditional methods that limit students' engagement and comprehension. Despite the global shift towards technology-driven learning, many lecturers encounter difficulties in adopting digital instructional tools, often due to inadequate facilities, poor internet access, unstable electricity supply, and limited technical skills. The study employed a descriptive survey design to examine the use, challenges, and effectiveness of digital instructional tools in English Language teaching in tertiary institutions. A sample of 160 lecturers was selected, and data were gathered using a validated self-structured questionnaire divided into demographic and research sections, with responses rated on a 4-point Likert scale. Reliability was established through Cronbach's alpha. Descriptive statistics such as frequency, percentage, mean, and standard deviation were used to analyze research questions, with 2.50 as the decision benchmark. Hypotheses were tested using ANOVA. The findings revealed that lecturers moderately utilized digital instructional tools in English Language teaching, with high usage of projectors, multimedia, and video resources (mean = 3.36–3.46). However, integration faced challenges such as unstable electricity (mean = 3.53), inadequate technology (3.25), poor internet (3.08), high maintenance cost (3.30), and need for training (3.29). Despite these, lecturers perceived digital tools as effective in enhancing engagement (3.22), improving comprehension (3.03), saving time (3.26), extending practice beyond class (3.26), and improving outcomes (3.32). ANOVA showed no significant differences in utilization ($p = .917$) or challenges ($p = .918$), but significant differences in effectiveness perceptions ($p = .022$). The study concludes that digital instructional tools are indispensable in English Language teaching and recommends improved institutional support, training, and provision of modern facilities to strengthen technology integration.

Keywords: *Artificial intelligence, emotional intelligence, self-awareness, mental health, Nigerian educational settings*

INTRODUCTION

The increased complexity of the social and emotional requirements of students has enhanced the alarm about the lack of mental-health care and the scarcity of systematic interventions aimed at the development of emotional intelligence and self-understanding in learning environments. Traditional guidance arrangements tend to be ineffective in the timely detection of emergent emotional issues, thus creating delayed interventions and increased psychological vulnerability in the learners. This situation highlights the urgent need of innovative, large-scale, and proactive processes which strengthen emotional support systems at school. The implementation of artificial intelligence (AI) to the creation of emotional intelligence (EI), self-awareness training, and mental-health (MM) monitoring offers solutions that can fill these gaps and enhance the overall learning outcomes (Shidhaye et al., 2015). AI improves emotional intelligence in schools through affective computing systems that are able to identify emotional signals and instruct learners to understand and control their moods.

The experiences of ICT-based learning environments in Nigeria show that technology contributes to the level of engagement among learners and creates the possibility of reflective socio-emotional development (Ikegbusi et al., 2021). Quality assurance issues in primary education also indicate the lack of the implementation of innovative tools that would develop the emotional abilities of students in addition to academic skills (Ezugoh et al., 2023). Educational pedagogy studies underscore the need to have adaptive strategies that foster holistic development of learners, thus, indicating that AI-based emotional coaching can enhance classroom interactions and lead to the development of empathy (Egwu, 2022). The problems related to handling institutional resources demonstrate the importance of AI tools that personalise learning and maintain the emotional stability of students (Egwu & Mbonu, 2023). Moreover, challenges related to the AI use highlight the necessity of systematic support of emotional intelligence models (Onuh et al., 2024). Altogether, these researches encourage the prospects of the use of AI-driven socio-emotional platforms to enhance emotional regulation, self-reflection, and student well-being in the Nigerian educational settings.

The field of self-awareness development can be operated by artificial intelligence (AI)-based solutions, including reflective learning analytics and digital self-assessment dashboards, which enable learners to track their thought patterns, behaviours, and performance patterns over time. Reports created through these platforms identify both strengths and weaknesses, as well as emotional tendencies and thus prompt learners to develop deliberate self-development strategies (Maralov et al., 2023). Students get a better understanding of the role of their emotions in academic performance through the constant-feedback loops, adopting a growth mindset and increasing their metacognitive skills, which promote prolonged resilience and personal growth.

AI also supports mental-health services in educational institutions through the early-warning systems that identify mental distress and depression indicators, burnout, or social isolation. Digital footprints examined by machine-learning models include learning behaviours, participation, language use and attendance, which can be used to predict any potential mental-health issues and warn counsellors to intervene in a timely manner (Peycheva et al., 2023). Psychologically assistive chatbots will be able to offer 24/7 support including coping techniques and refer students to a mental health professional when needed. These tools do not in any way displace human counsellors but serve to supplement their services, ease congestion points on services and make them more accessible.

AI-based mental-health systems enhance the ability of teachers and administrators to establish emotionally supportive learning systems by real-time insights that enable them to understand behavioural trends, predictive stress responses, and customised interventions. The literature on institutional governance in Nigeria demonstrates that there are still significant gaps in monitoring mechanisms that require the use of data-driven instruments to improve human decision-making and responsiveness (Okonkwo & Idigo, 2022). Wider discourses about the changing socio-digital world in Africa underscore the applicability of technology uptake in emerging psychosocial issues in young people (Adolphus et al., 2023). The literature on political engagement and social media shows that social media can influence behavioural patterns, and thus provide an example of how AI can be used to monitor emotional trends and control responsible interaction (Ozeh et al., 2023). The research findings on innovation in the public-sector also evidenced how digital systems enhance resource management and responsiveness (Onwunyi et al., 2023) and thus validated the argument that AI could strengthen the infrastructure of emotional support in schools. The vulnerabilities related to conflicts also aid the argument of the relevance of trauma-informed strategies in the institutional context, which supports the importance of AI tools in helping teachers detect and address psychological distress (Ochi et al., 2022).

In spite of these advantages, AI application in emotional and mental-health scenarios presents ethical issues. Such factors as data privacy, bias in algorithms, and the danger of excessive reliance on digital emotional monitoring are essential issues that require proper management. The necessity to explore AI implementation in emotional intelligence, self-awareness, and mentalhealth in Nigerian educational institutions arises due to the urgency to reinforce supporting students in schools. Most institutions are still grappling with emotional and behavioural issues among the learners and they use conventional counselling strategies that often cannot detect and intervene in time. Despite the growing interest in AI regarding its role in the delivery of instructions, not much research is done on how AI-based instruments can influence socio-emotional development in Nigeria, thus leaving a gap in knowledge on how AI-based tools can modify the emotional intelligence of students (Bali et al., 2024; Oluyemisi, 2023). Such a gap emphasizes the need to investigate the role of emotion - recognition systems, adaptive socio-emotional learning platforms, and intelligent feedback mechanisms on the emotional development of learners.

There are no well-structured digital avenues to guide students towards developing more profound self-understandings. Although digital technologies are increasingly taking center-stage in schools, there remains a lack of sufficient empirical evidence that can help understand how AI-powered analytics can benefit students in understanding their emotional patterns, behavioural tendencies, and personal strengths in learning conditions in Nigerian schools (Okunade, 2024). The relationship is critical to comprehend to enhance reflective learning and build more adaptive student behaviour. The growing anxiety about the deteriorating state of student mental-health gives additional weight to the necessity of this enquiry. Some students feel stressed, anxious and feel socially withdrawn, but Nigerian schools are almost never equipped with effective monitoring devices and enough counselling staff. Whereas world literature points to the applicability of AI in early detection and emotional support, there is still little local literature on AI-based mental-health outcomes (Olawade et al., 2024). All these gaps contribute to the justification of the study and the significance of studying the role of AI in enhancing the holistic well-being of Nigerian students.

Research Questions

1. What is the influence of artificial intelligence–based tools on the development of emotional intelligence among students in Nigerian educational settings?
2. How does the integration of artificial intelligence enhance students' self-awareness in Nigerian schools?
3. What effect does the use of artificial intelligence have on students' mental health outcomes in Nigerian educational institutions?

METHOD

The current research used a descriptive survey design to explore AI impact on emotional intelligence, self-awareness, and mental health outcomes in students in learning institutions in Nigeria. The design was chosen because of its capacity to measure naturally occurring phenomena, and because it provided measurable data of representative sample. The population of interest included secondary and tertiary students in Nigeria. The sample size of 70 respondents was obtained with the help of a purposive sampling approach that guaranteed representation in terms of institutional types and the level of education. This method offered specific information about the effects of AI integration in specific educational levels. Three main constructs, including emotional intelligence, self-awareness, and mental health outcomes, and the level of AI use in academic pursuits, were assessed using a structured questionnaire, including a Likert-type scale. The gathered data were analyzed with the help of SPSS version 25. Demographic variables were summarized by using descriptive statistics (frequencies and percentages). Pearson correlation analysis, multiple regression analysis, ANOVA and collinearity diagnostics were used as inferential procedures to test relationships and predictive effects of AI use and institutional type on the targeted outcomes. Regression assumptions, especially of multicollinearity, were tested using VIF, tolerance values, and condition indices. The ethical aspects were strongly regarded. The participants were well aware of the objectives of the study, and their involvement was voluntary, with the promise of confidentiality.

RESULTS AND DISCUSSION

Table 1.
Distribution of Respondents by Type of Institution (N = 70)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Public	24	34.3	34.3	34.3
	Private	46	65.7	65.7	100.0
	Total	70	100.0	100.0	

Table 1 shows that the majority of respondents (n = 46, 65.7%) attend private institutions, while 24 respondents (34.3%) are from public institutions. This indicates that the sample is skewed toward private schools, which may influence the study findings, particularly in analyses involving institutional differences.

Table 2.
Distribution of Respondents by Educational Level (N = 70)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Secondary	24	34.3	34.3	34.3
	Tertiary	46	65.7	65.7	100.0
	Total	70	100.0	100.0	

Table 2 shows that most respondents are tertiary students (n = 46, 65.7%), while 24 respondents (34.3%) are in secondary schools. This suggests the sample is predominantly composed of higher education students, which may influence responses, particularly regarding exposure to artificial intelligence tools and experiences with self-awareness and mental health outcomes.

Research Question 1: What is the influence of artificial intelligence–based tools on the development of emotional intelligence among students in Nigerian educational settings?

Table 3.
Pearson Correlation between Emotional Intelligence, Artificial Intelligence Use, and Type of Institution among Students (N = 70)

		Emotional Intelligence	Artificial Intelligence Use	Type of institution
Pearson Correlation	Emotional Intelligence	1.000	.343	.349
	Artificial Intelligence Use	.343	1.000	-.072
	Type of institution	.349	-.072	1.000
Sig. (1-tailed)	Emotional Intelligence	.	.002	.002
	Artificial Intelligence Use	.002	.	.277
	Type of institution	.002	.277	.
N	Emotional Intelligence	70	70	70
	Artificial Intelligence Use	70	70	70
	Type of institution	70	70	70

Table 3 shows a positive and significant relationship between artificial intelligence use and emotional intelligence (r = [.343], p = [.002], N = [70]). Type of institution is also positively related to emotional intelligence (r = [.349], p = [.002]). However, AI use and institution type are weakly and negatively related (r = [-.072], p = [.277]).

Table 4.
Analysis of Variance Showing the Joint Predictive Effect of Artificial Intelligence Use and Type of Institution on Emotional Intelligence

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	167.181	2	83.590	11.649	.000[b]
	Residual	480.762	67	7.176		
	Total	647.943	69			
a. Dependent Variable: Emotional Intelligence						
b. Predictors: (Constant), Type of institution, Artificial Intelligence Use						

The ANOVA result in Table 4 indicates that the model is statistically significant (F = [11.649], p = [.000], df = [2, 67]). The predictors explain a notable portion of variance, with a regression sum of squares ([167.181]) higher than expected by chance. The residual variance ([480.762]) confirms that other unmeasured factors still contribute.

Table 5.
Multiple Regression Coefficients for Artificial Intelligence Use and Type of Institution on Emotional Intelligence

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	4.017	2.372		1.694	.095	-.717	8.751					
	Artificial Intelligence Use	.440	.126	.370	3.504	.001	.189	.690	.343	.394	.369	.995	1.005
	Type of institution	2.410	.676	.376	3.563	.001	1.060	3.759	.349	.399	.375	.995	1.005
a. Dependent Variable: Emotional Intelligence													

Artificial intelligence use significantly in Table 5 predicts emotional intelligence (B = [.440], β = [.370], t = [3.504], p = [.001]). Type of institution also shows a strong effect (B = [2.410], β = [.376], t = [3.563], p = [.001]). The constant is not significant (B = [4.017], p = [.095]). VIF values ([1.005]) show no multicollinearity.

Table 6.
Inter-Correlation and Covariance between Type of Institution and Artificial Intelligence Use

Model			**Type of institution**	**Artificial Intelligence Use**
1	Correlations	Type of institution	1.000	.072
		Artificial Intelligence Use	.072	1.000
	Covariances	Type of institution	.457	.006
		Artificial Intelligence Use	.006	.016
a. Dependent Variable: Emotional Intelligence				

Table 6 shows that the correlation between artificial intelligence use and type of institution is weak (r = [.072]) and insignificant. The low covariance values for both variables ([.006] and [.457]) indicate minimal shared variance. This supports the interpretation that each variable independently contributes to emotional intelligence without overlapping influence in the regression model.

Table 7.
Collinearity Diagnostics for the Predictors of Emotional Intelligence

				Variance Proportions		
Model	Dimension	Eigenvalue	**Condition Index**	**(Constant)**	**Artificial Intelligence Use**	**Type of institution**
1	1	2.930	1.000	.00	.00	.01
	2	.059	7.033	.02	.12	.82
	3	.011	16.275	.98	.88	.17
a. Dependent Variable: Emotional Intelligence						

Table 7 shows that the highest condition index recorded is ([16.275]), which is well below the critical threshold of [30]. The eigenvalues ([2.930], [.059], [.011]) suggest good data structure. Variance proportions are distributed across dimensions, confirming that multicollinearity is not a threat and that the independent variables are stable and reliable.

Research Question 2: How does the integration of artificial intelligence enhance students' self-awareness in Nigerian schools?

Table 8.
Pearson Correlation between Self-Awareness, Artificial Intelligence Use and Type of Institution (N = 70)

		Self-Awareness	Artificial Intelligence Use	Type of institution
Pearson Correlation	Self-Awareness	1.000	.719	-.007
	Artificial Intelligence Use	.719	1.000	-.072
	Type of institution	-.007	-.072	1.000
Sig. (1-tailed)	Self-Awareness	.	.000	.477
	Artificial Intelligence Use	.000	.	.277
	Type of institution	.477	.277	.
N	Self-Awareness	70	70	70
	Artificial Intelligence Use	70	70	70
	Type of institution	70	70	70

From Table 8, AI use has a strong, positive, and significant relationship with self-awareness (r = [.719], p = [.000]), showing that increased AI integration corresponds with higher self-awareness levels. Type of institution shows a very weak and insignificant relationship with self-awareness (r = [-.007], p = [.477]). AI use and institution type are also weakly related (r = [-.072], p = [.277]).

Table 9.
ANOVA for the Joint Influence of Artificial Intelligence Use and Type of Institution on Students' Self-Awareness

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	441.164	2	220.582	36.087	.000[b]
	Residual	409.536	67	6.112		
	Total	850.700	69			
a. Dependent Variable: Self-Awareness						
b. Predictors: (Constant), Type of institution, Artificial Intelligence Use						

The ANOVA in Table 9 reveals that the model significantly predicts self-awareness (F = [36.087], p = [.000], df = [2, 67]). The regression sum of squares is [441.164], compared with a residual sum of squares of [409.536], indicating that AI use and institution type together explain a substantial proportion of variance in students' self-awareness scores.

Table 10.
Multiple Regression Coefficients Showing the Contribution of Artificial Intelligence Use and Type of Institution to Self-Awareness

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.176	2.189		.081	.936	-4.193	4.546					
	Artificial Intelligence Use	.984	.116	.722	8.495	.000	.753	1.215	.719	.720	.720	.995	1.005
	Type of institution	.331	.624	.045	.530	.598	-.915	1.577	-.007	.065	.045	.995	1.005
a. Dependent Variable: Self-Awareness													

AI use in Table 10 is a strong and significant predictor of self-awareness (B = [.984], β = [.722], t = [8.495], p = [.000], CI = [.753–1.215]). Type of institution is not significant (B = [.331], β = [.045], t = [.530], p = [.598]). The constant is also insignificant (B = [.176], p = [.936]). VIF values ([1.005]) indicate no multicollinearity.

Table 11.
Inter-Correlation and Covariance between Artificial Intelligence Use and Type of Institution

Model			Type of institution	Artificial Intelligence Use
1	Correlations	Type of institution	1.000	.072
		Artificial Intelligence Use	.072	1.000
	Covariances	Type of institution	.390	.005
		Artificial Intelligence Use	.005	.013
a. Dependent Variable: Self-Awareness				

The correlation between AI use and type of institution in Table 11 is weak (r = [.072]). Covariance values are low ([.005] and [.390]), indicating minimal shared variance between the predictors. This confirms that both variables operate independently in the model and do not distort each other's contribution to explaining students' self-awareness levels significantly.

Table 12.
Collinearity Diagnostics for Predictors of Students' Self-Awareness

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Artificial Intelligence Use	Type of institution
1	1	2.930	1.000	.00	.00	.01
	2	.059	7.033	.02	.12	.82
	3	.011	16.275	.98	.88	.17
a. Dependent Variable: Self-Awareness						

The eigenvalues ([2.930], [.059], [.011]) and condition indices ([1.000], [7.033], [16.275]) in Table 12 are within acceptable statistical limits. The highest condition index ([16.275]) is below the critical value of [30], confirming the absence of multicollinearity. Variance proportions are properly distributed, validating the stability of the regression model.

Research Question 3: What effect does the use of artificial intelligence have on students' mental health outcomes in Nigerian educational institutions?

Table 13.
Correlation Matrix of Mental Health Outcomes, Artificial Intelligence Use and Type of Institution

		Mental Health Outcomes	Artificial Intelligence Use	Type of institution
Pearson Correlation	Mental Health Outcomes	1.000	.672	.015
	Artificial Intelligence Use	.672	1.000	-.072
	Type of institution	.015	-.072	1.000
Sig. (1-tailed)	Mental Health Outcomes	.	.000	.452
	Artificial Intelligence Use	.000	.	.277
	Type of institution	.452	.277	.
N	Mental Health Outcomes	70	70	70
	Artificial Intelligence Use	70	70	70
	Type of institution	70	70	70

Artificial Intelligence Use in Table 13 shows a strong positive and statistically significant relationship with Mental Health Outcomes ($r = 0.672$, $p = 0.000$, $n = 70$). This suggests that higher levels of AI use are associated with better mental health. Type of Institution shows a very weak, non-significant correlation ($r = 0.015$, $p = 0.452$).

Table 14.
ANOVA Summary of Multiple Regression Predicting Mental Health Outcomes

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	387.379	2	193.689	28.055	.000[b]
	Residual	462.564	67	6.904		
	Total	849.943	69			
a. Dependent Variable: Mental Health Outcomes						
b. Predictors: (Constant), Type of institution, Artificial Intelligence Use						

The regression model in Table 14 is statistically significant (F(2,67) = 28.055, p = 0.000). The predictors explain approximately 45.6% of the total variance in mental health outcomes (387.379 ÷ 849.943 = 0.456). This indicates that Artificial Intelligence Use and Type of Institution together have a strong predictive influence.

Table 15.
Regression Coefficients of Artificial Intelligence Use and Type of Institution on Mental Health Outcomes

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.667	2.326		.287	.775	-3.977	5.310					
	Artificial Intelligence Use	.922	.123	.677	7.489	.000	.676	1.168	.672	.675	.675	.995	1.005
	Type of institution	.464	.663	.063	.700	.486	-.860	1.788	.015	.085	.063	.995	1.005
a. Dependent Variable: Mental Health Outcomes													

Artificial Intelligence Use in Table 15 is a significant predictor of Mental Health Outcomes (B = 0.922, β = 0.677, t = 7.489, p = 0.000). A one-unit increase in AI use raises mental health scores by 0.922 units. Type of Institution is not significant (B = 0.464, p = 0.486).

Table 16.
Coefficient Correlation Matrix of Predictors of Mental Health Outcomes

Model			Type of institution	Artificial Intelligence Use
1	Correlations	Type of institution	1.000	.072
		Artificial Intelligence Use	.072	1.000
	Covariances	Type of institution	.440	.006
		Artificial Intelligence Use	.006	.015
a. Dependent Variable: Mental Health Outcomes				

The correlation between Artificial Intelligence Use and Type of Institution is very low (r = 0.072) as captured in Table 16, indicating minimal association between the independent variables. Covariance values of 0.440 and 0.015 further suggest that the predictors do not strongly overlap, confirming the reliability of the regression results.

Table 17.
Collinearity Diagnostics of Predictors of Mental Health Outcomes

				Variance Proportions		
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Artificial Intelligence Use	Type of institution
1	1	2.930	1.000	.00	.00	.01
	2	.059	7.033	.02	.12	.82
	3	.011	16.275	.98	.88	.17
a. Dependent Variable: Mental Health Outcomes						

The highest condition index in Table 17 is 16.275, which is below the critical threshold of 30. Variance proportions are distributed across dimensions. The tolerance values (0.995) and VIF values (1.005) confirm absence of multicollinearity, indicating stable and reliable regression coefficients in the model.

Discussion

The initial research question was devoted to the impact of AI-based tools on emotional intelligence. The findings showed that there was a positive and significant correlation between AI use and emotional intelligence ($r = .343$, $p = .002$) and type of institution also had a significant positive association ($r = .349$, $p = .002$). The use of AI also significantly predicted emotional intelligence (B= -.440, b=.370, p=.001), along with type of institution (B= 2.410, b=.376, p=.001) with little multicollinearity (VIF=1.005). These results indicate that students that utilize AI-based instruments exhibit greater emotional intelligence, irrespective of the type of institution. This is supported by studies that show AI-based emotional support systems improve affective capabilities and emotional control of learners (D'Silva and Pande, 2024). Conversely, other researchers have also observed that AI can be emotionally disengaged in case of poor implementation, and that the design and integration quality are key (Lin and Chen, Q. (2024)). Similarly, AI companion users stated that they had enhanced self-reflection and socio-emotional growth (Sethi and Jain, 2024).

The second research question was the incorporation of AI and self-awareness of students. Correlation analysis indicated that there was a significant positive correlation between AI use and self-awareness ($r = .719$, $p = .000$), but a very weak, non-significant correlation between type of institution and self-awareness ($r = -.007$, $p = .477$). The regressions findings were able to verify that AI use was a significant predictor of self-awareness (B 0.984, -0.722, p 0.000), with the institutional type being insignificant. Such findings suggest that AI tools have an independent effect of increasing self-awareness. This result is consistent with the articles that show that AI-based applications, including personalized journaling apps, help improve reflective practice and metacognitive awareness (Nebal et al., 2024). On the contrary, conventional teaching methods that do not incorporate AI usage have lower rates of self-awareness among learners, which indicates that AI makes a distinct contribution to personal development in education.

The third research question concerned the impact of AI on outcomes in mental health. The results showed a strong, positive, and significant correlation between the AI use and the mental health outcome ($r = .672$, $p = .000$), but not between the type of institution ($r = 0.015$, $p = 0.452$). Results of the regression helped verify that AI use is a significant predictor of mental health outcomes ($B = .922$, $\beta = .677$, $p = .000$). These results reveal that the integration of AI is linked to better mental health in students. It aligns with the literature that discusses the use of AI as the source of empathic interaction and emotional support, which improve mental health in educational environments (Sharma et al., 2022; Oluyemisi, 2023). Conversely, schools without AI integration might be incapable of offering similar levels of psychosocial support thus restricting mental health advantages to students (Olawade et al., 2024). The research reveals that AI-based technologies always have a beneficial impact on emotional intelligence, self-awareness, and mental health outcomes of Nigerian students. Although each type of institution is somewhat less influential, the impact of AI alone is substantial, which is consistent with the new evidence on the AI-enhanced socio-emotional and psychological support aspects of education.

CONCLUSION

The research determined that artificial intelligence (AI) implementation in Nigerian learning environments impacts positively and substantially the emotional intelligence levels of students, their self-awareness, and mental wellbeing. The results indicated that AI utilization is a strong indicator of emotional intelligence, which improves students by improving their ability to perceive, manage, and respond to emotions. In the same vein, AI integration was demonstrated to significantly enhance self-awareness, which allows learners to think reflectively and build a wider perspective of their own and academic behaviours. In addition, AI application is positively associated with improved mental health outcomes, which indicates that AI-based interventions have the potential to support emotional well-being, decrease stress, and enhance psychological comfort. In contrast, the nature of an institution was not typically relevant, which means that the advantages of AI are not limited to institutional settings. The findings highlight the disruptive nature of AI as the means of developing the holistic student and, especially, enhancing socio-emotional proficiencies and psychological well-being. The paper confirms that the thoughtful and planning use of AI technologies within pedagogical settings can positively affect the general quality of learning experience, providing students with the critical emotional and cognitive skills relevant to academic achievement and self-development.

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