

Artificial Intelligence Adoption Drivers and Accounting and Banking and Finance Students' Performance in Dennis Osadebay University, Nigeria

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Abstract

The emergence of artificial intelligence (AI) has transformed the educational sector globally. However, most Nigerian Universities are yet to fully integrate AI into their curriculum. Succinctly, this research examines the effect of five key AI adoption drivers on accounting and finance students' performance. Emphasis was placed on the extent to which app intuitiveness, peer group pressure, institutional leadership readiness, external support, and student adaptability influence accounting and finance students' performance. The study surveyed 390 male and female accounting and banking and finance students at Dennis Osadebay University, Asaba. This study adopts a quantitative research design. The drafted questionnaire was given to two (2) accounting and finance experts to review using the Index of Item-Objective Congruence (IOC) method. Meanwhile, a pilot test with 40 accounting and finance students confirmed that the survey instrument is reliable. The data were analysed by using Structural Equation Modelling (SEM). The findings indicate that peer group pressure, institutional readiness, and student adaptability significantly influence AI adoption, while app intuitiveness and external support do not. In like manner, AI adoption strongly affects the performance of accounting and banking and finance students. This study provides valuable insights that can drive policy formulation in the global university system. Also, the study provide rich insight on how ethical usage of AI can be achieved in the Nigerian context by emphasising the roles of peer group pressure, institutional readiness, and student adaptability in improving students 'academic performance.

Keywords: App intuitiveness, peer group pressure, institutional leadership readiness, external support, student adaptability, students' academic performance

1. Introduction

Recently, there is an increasing volume of academic research on the instrumental roles of AI in enhancing both lecturing and mentoring across various disciplines (Phongsatha, 2024; Panigrahi, 2020; Razak et al., 2023; Uriri & Mmom, 2025). As expected, AI tools make teaching and the learning process worthwhile by providing smart lecturing systems which adapt to each student's learning style, facilitating predictive analytics to monitor each student's progress, enabling automated grading systems and encouraging personalised learning experiences targeted at meeting each student's needs (Bali et al., 2024; Chen et al., 2020). Another major advantage of AI adoption is that it improves students' autonomy and engagement. Justifiably, AI offers a promising avenue to bolster digital fluency, analytical competence, and critical decision-making skills among accounting and finance students. However, such benefits attributed to AI adoption are largely factored by students' behavioural dispositions, institutional readiness, and external supports. Hence, understanding how these multidimensional factors influence AI adoption particularly in newly established universities like Dennis Osadebay University (DOU), are highly germane.

While earlier studies in advanced countries, such as the studies of Vongurai (2025); Shang et al. (2023), Kar et al. (2021), Cubric (2020); & Knox (2020) abound, limited research exists on how AI adoption drivers affect student-academic performance in developing economies, especially Nigeria. Even studies conducted in the Nigerian context, such as the studies of Abubakar et al. (2024), Adewale et al. (2024), Bali et al. (2025), and Obomeghie (2025), did not focus on five key drivers: app intuitiveness, peer group pressure, institutional leadership commitment, external

supports, organisational readiness and student adaptability. The current study, however, bridges the identified gap by focusing specifically on how these five key AI adoption drivers influence student academic performance. Hence, this research addresses the contextual and infrastructural realities unique to developing countries.

This study makes a unique contribution to digital education and AI literature by evaluating the interplay among AI adoption drivers (competitive pressure, institutional leadership commitment, organisational readiness, and external supports) and students' academic performance in technologically evolving yet highly challenging environment. Theoretically, this study contributes to the Technology-Organisation-Environment (TOE) model by incorporating an individual-level perspective (students' adaptability) into the model. This further enhances the explanatory power of the TOE model and supports its adaptability to AI research in emerging countries. Again, the study will provide a contextual roadmap for enhancing students' academic performance in the Nigerian context. Lastly, the study offers valuable insights for tertiary institutions, the Ministry of Higher Education (MHE), the Nigerian University Commission (NUC), and technology stakeholders (TS) on how they can best optimise AI adoption strategies to foster innovation in Nigeria's digital education landscape.

2. Literature Review

This research placed emphasis on the extent app intuitiveness, peer group pressure, institutional leadership readiness, external support, and student adaptability influences Accounting and Finance students' performance. The research was grounded on the TOE framework to explain technological factors (app intuitiveness and peer group pressure), organisational factors (institutional leadership readiness), environmental factors (external support), and individual-level factor (students adaptability) jointly influence accounting and banking and finance students' academic performance from an emerging country's university context.

Technology–Organization–Environment (TOE) Framework

The TOE framework developed by Tornatzky and Fleischer in 1990 served as the anchor theory. This theory analyzes how the five AI adoption drivers (app intuitiveness, peer group pressure, institutional leadership readiness, and external support) influence the target students' performance.

App Intuitiveness (API) and AI Adoption

(Vieriu and Petrea (2025) defined App intuitiveness as how fast students use AI-enabled learning platforms with less supervision. Intuitive AI-enabled learning platforms improve students' perceived ease of use, and in turn increase their frequency of use. Available research reports that user-friendly interfaces, engaging features, and clear navigation improve students' overall academic performance (Ajagunna, & Isaruk, 2022; Khasawneh & Khasawneh, 2023; Demir et al, 2023; Alneyadi et al., 2023). However, when AI-enabled learning software is poorly designed, it can make the learning process uninteresting, reduce students' motivation to learn, and ultimately lower their academic performance (Ajagunna et al., 2022; Demir & Akpinar, 2018; Koohestani et al., 2018). By implication, app intuitiveness is a major factor influencing AI adoption rates. Hence, the paper hypothesizes:

H₁: App intuitiveness readiness is a positive AI adoption driver.

Peer Group Pressure (PGP) and AI Adoption

One of the major factor influencing AI adoption rate is peer group pressure (PGP) among students. Studies indicate that students are more likely to use AI-enabled apps if they observe their peers are using and endorsing them (Korchak et al., 2025; Ramadhan & Usman, 2025). Such influences reduces become more evident during the initial stages of AI adoption. During this stage, students' opinions about the offerings of the AI are formed. Notably, PGP could either be positive or negative. A positive PGP encourages students to use AI ethically and by extension improves students' academic performance (Ramadhan & Usman, 2025). Meanwhile, negative PGP leads to over-reliance on AI and possibly academic dishonesty (Vieriu & Petrea, 2025; Zhai et al., 2024; Nguyen & Goto, 2024). This ultimately hinders students' academic performance. Hence, the study hypothesizes:

H₂: Peer group pressure is a positive AI adoption driver.

Institutional Leadership Readiness and AI Adoption

Institutional leadership readiness captures an institution's preparedness in terms of infrastructural capacity, internal policies, its readiness to accept and encourage effective use of AI, and the availability of digital resources that are paramount towards successful integration/adoption of AI into the academic system (Jamil et al., 2025; Jan et al., 2024; Lada et al., 2021). Available studies reported that organizational readiness is a positive driver of AI adoption. By implication, firms with high readiness levels are most likely to adopt AI than firms that with low readiness level (Çınar et al., 2021). The rationalization is that firms with high readiness level have the requisite capabilities to integrate AI into their

business operation (Jamil et al., 2025; Jan et al., 2024; Lada et al., 2023). In the Nigerian educational setting, high technological readiness increases AI adoption rate. Therefore, this study proposes the following hypothesis:

H₃: Institutional Leadership readiness is a positive AI adoption driver.

External support

Another critical factor which determines the success or failure of AI adoption is external support. External support stems from vendors, contractors, consulting companies, donor firms inter alia determines the success or failure of AI adoption. Justifiably, external funding for capacity building, digital literacy programs, and internet access improves AI adoption by reducing barriers that militate against AI adoption. Prior studies clearly evidenced that a technological preparedness in terms of clear communication improves AI adoption especially within low-resource environments (Felemban et al., 2024; Najdawi, 2020; Chen et al., 2019; Alsheibani et al., 2018). However, lack of external support has the capacity to reduce AI adoption rate (Uren & Edwards, 2023). Therefore, this study proposes the following hypothesis:

H₄: External support is a positive AI adoption driver.

Student Adaptability and AI Adoption

Student adaptability is conceptualized as the students' ability to learn, unlearn, and relearn new technologies. It encompasses students' cognitive flexibility, openness to change, and resilience, all of which influence students' willingness to explore new technologies and integrate AI software into the learning process consistently (Zhou, Chen, & Park, 2025). The justification is that, students' adaptability enable students to respond to technological disruptions with resilience and enthusiasm rather than either resistance or anxiety (Ward et al, 2025; Yaseen et al., 2025; Hao et al., 2025). Consequently, the more students adapt to AI, the more the extent of AI adoption increase greatly. Therefore, this study proposes the following hypothesis:

H₅: Student adaptability is a positive AI adoption driver.

AI Adoption and Students' Academic Performance

AI adoption is highly beneficial to students as it help to improve learning outcomes. AI improves students' performance by providing learning pathways that are personalized. Also, AI introduces intelligent automated grading, efficient teaching systems, and predictive analytics that are targeted at improving students' performance level (Badghish & Soomro, 2024). These enable lecturers to identify students' learning patterns, and intervene accordingly (Duan et al., 2019). Phongsatha (2024) & Verma et al. (2024) added that, AI adoption improves students' academic performance in various emerging countries, as elsewhere, by improving the feedback mechanisms, encouraging adaptive assessments, and enabling efficient curriculum delivery. Given these identified benefits, this study proposes:

H₆: AI adoption has a positive significant effect on students' academic performance.

Conceptual Framework

This study's conceptual model was designed using insights gained from the integration of the TOE framework with insights from both empirical studies and Nigerian higher education realities in line with the submissions of Badghish and Soomro (2024). The model hypothesizes that the five key AI adoption drivers jointly influence AI adoption, which subsequently impacts DOU accounting and finance students' academic performance. Figure 1 presented the conceptual framework of this study.

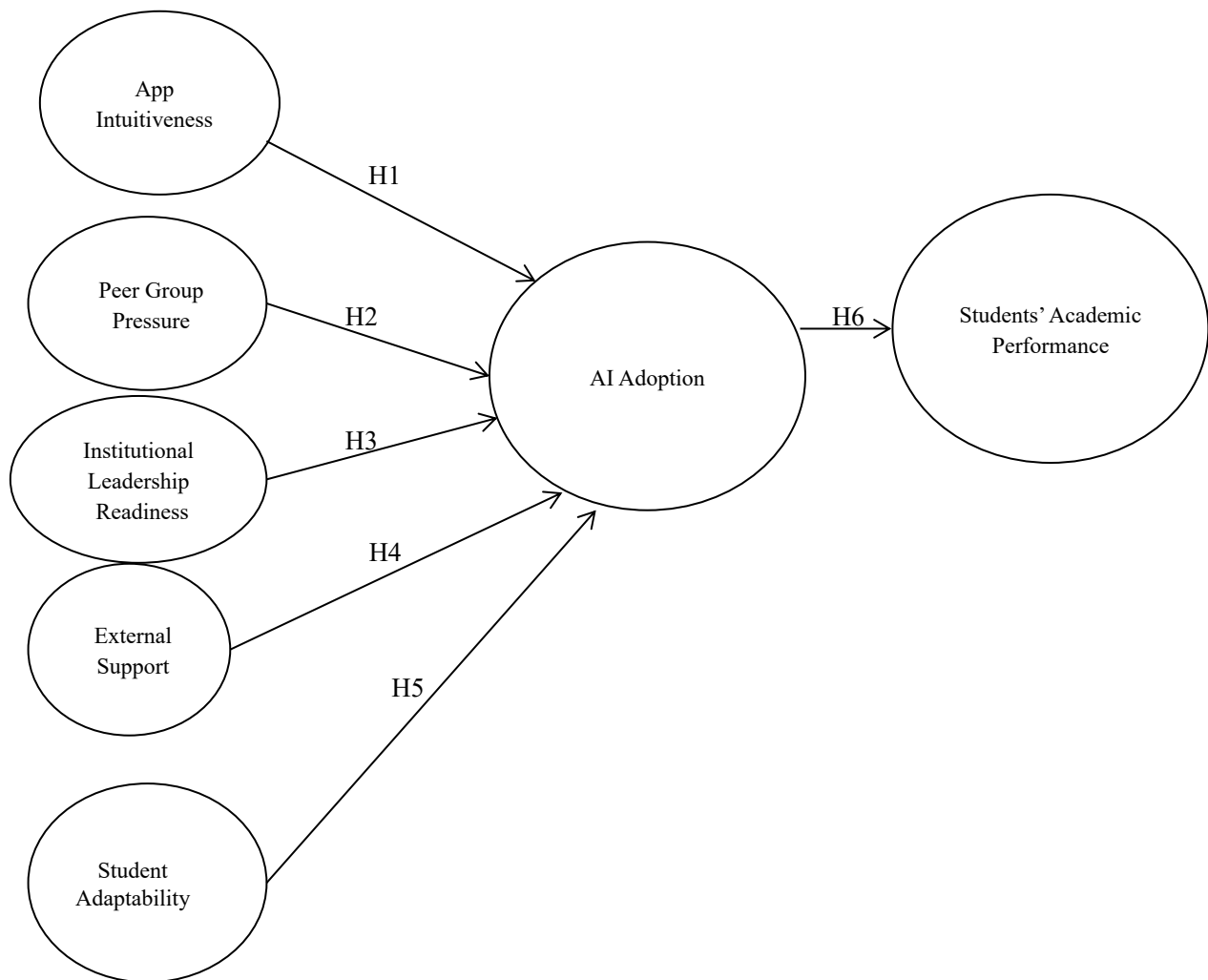


Figure 1. Proposed Conceptual Framework

3. Methodology

Research Design

This study adopts a quantitative research design to examine the effect of AI adoption drivers (app intuitiveness, peer group pressure, institutional leadership commitment, external supports, organisational readiness and student adaptability) on accounting and banking and finance students' academic performance at DOU. Justifiably, a quantitative research design is appropriate for the study given the fact that it allows for the collection of numeric data, allows testing statistical relationships among variables, and enhances the generalization of findings to a wider student population. More so, the use of a structured questionnaire to elucidate information from the students aligns with the goal of quantifying the influence of AI adoption drivers on accounting and banking and finance students' academic performance.

Target Population and Sample Size

Our target population consisted of accounting and banking and finance undergraduate students in 200 to 400-level classes during the second semester of the 2024/2025 academic session. This group consisted of a total of 450 students. These groups were chosen based on academic maturity, exposure to financial literacy courses and entrepreneurial content within the university curriculum. Meanwhile, a total of three hundred and ninety (390) accounting and banking and finance undergraduate students were sampled. Our sample size falls within the recommendation of Hair et al. (2013), stressing that a minimum sample size of 200 is acceptable for structural equation modelling (SEM).

Measurement Items Development

A well-structured questionnaire served as the primary source of data collection. The structured questionnaire was developed using Google Docs while the published link was sent to the departmental WhatsApp group of the students. The questionnaire comprised twenty-three items developed from validated instruments in existing digital education

literature. Each of the variables has at least three items on a 5-point Likert scale. Specifically, 1 designated strongly disagree, 2 was designated disagreed, 3 was designated neutral, 4 was designated agreed, while five was designated strongly disagreed. For example, peer group pressure was measured by items such as “my peer group motivates me to adopt AI tools” as developed by Ngonso et al (2025).

Students’ academic performance served as a dependent variable and was assessed through items like "Since I have been using AI tools, my Cumulative Grade Point Average (CGPA) has improved." (Baashar et al, 2022). To ensure that the questionnaire items are valid, the developed questionnaire was given to two (2) accounting and finance experts to review using the Index of Item-Objective Congruence (IOC) method. Items scoring above 0.70 were retained. Meanwhile, 40 accounting and banking and finance students were pilot surveyed.

Data Collection and Sampling Procedure

Data were collected between June 20th and July 7th, 2025, using the convenience and stratified sampling techniques. While stratification was based on the students' academic level (200 to 400 level), the students were conveniently sampled using their departmental WhatsApp group. Before the students answered the questionnaire, their consents were obtained.

4. Data Analysis

The study used Confirmatory Factor Analysis (CFA) to test the suitability of the measurement model while Structural Equation Modelling (SEM) was used to test the research hypothesis. The various model fit tests conducted include Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA) in line with the submissions of Hair et al. (2013). Path coefficients were computed to examine the direction (positive or negative) between AI adoption drivers and accounting, banking and finance students’ academic performance while the p-value was computed to test the statistical significance of these relationships.

Ethical Considerations

We conducted the research in line with the ethical standards which guide research in DOU. First, we ensures that the students voluntarily agreed to participate in the research before we sent the questionnaire to them to fill. Also, we assured them that the questionnaire is for the purposes of research and that their identity will be highly confidential and anonymous.

5. Results

Table 1 presents the demographic analysis of the students. A total of 390 samples were collected from 200 level to 400 level in Dennis Osadebay University, Asaba. From Table 1, the sample comprised 131 males and 259 females. This composition adequately represents the target student population for this study. Also, the respondents fall within the four (4) age brackets: of 18 to 21 years, 22 to 25 years, 26 to 29 years, and 30 years and above. Specifically, 69.25% of the students were within the ages of 18 and 21 years, 17.54% were within the ages of 22 and 25 years, 7.90% were within the ages of 26 and 29 years, while 5.31% were within the ages of 30 years and above (Figure 2).

Table 1. Respondents’ Demographic Distribution (n=390)

Sex	Frequency (F)	Percentage (%)
Males	131	33.59
Females	259	64.41
Age Bracket	Frequency (F)	Percentage (%)
18-21	270	69.25
22-25	68	17.54
26-29	31	7.90
30 and Above	21	5.31

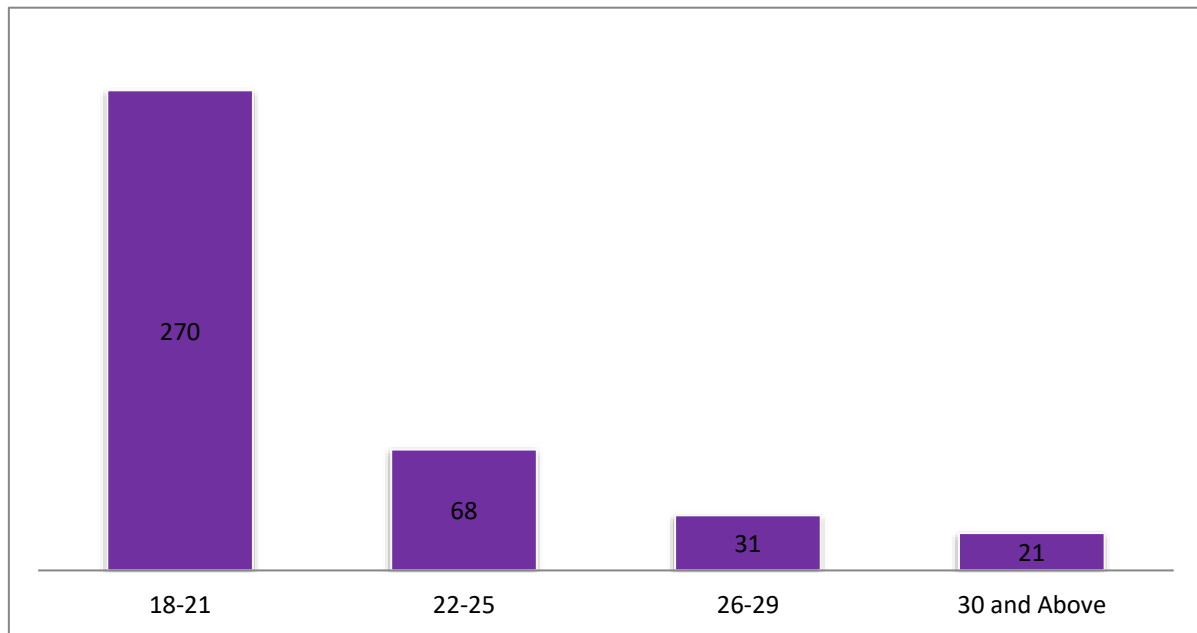


Figure 2. Respondents' Age Distribution

Reliability of the Measures

Table 2 shows the construct reliability of the variables under review. Cronbach's alpha and composite reliability were used to test for the construct reliability. Within the SEM PLS analysis context, an instrument is considered internally consistent if its Cronbach's Alpha (CA) value exceeds .70 and its Composite Reliability (CR) value also exceeds .70. From Table 2, the constructs reported Cronbach's alpha values range from .884 to .928, which are considered good to exceptional (Tavakol & Dennick, 2011). Also, FL values of API range between .752 and .891, FL values of PGP range between .701 and .864, FL values of ILR range between .808 and .901, FL values of EXS range between .736 and .885, and FL values of STD range between .701 and .872. The CR values in the table vary from 0.896 to 0.950, which are regarded as good to exceptional.

Table 2. Reliability of the Measures

Construct	Questionnaire Source	Number of Items	CA	CR	FL Range
API	Vieriu and Petrea (2025); Ngonso et al (2025). Korchak et al. (2025)	3	.910	.943	.752–.891
PGP		4	.875	.915	.701–.864
ILR		4	.928	.954	.808–.901
EXS	Badghish and Soomro (2024); Baashar et al, (2022)	5	.902	.935	.736–.885
AIA		3	.880	.872	.762–.891
STD		4	.884	.922	.701–.872

Note: Cronbach Alpha (CA); Factor Loading (FL); Composite Reliability (CR), and Average Variance Extracted (AVE)

Validity of the Measures

Tables 3 and 4 show the convergent and discriminant validity of the five AI adoption drivers and students' academic performance measure. Average Variance Extracted (AVE) was used to test for the convergent validity, while the Fornell-Larcker criterion (FLC) was used to test for the discriminant validity of the five AI adoption drivers and students' academic performance measure. Within the SEM PLS analysis context, an instrument is considered valid if its AVE value exceeds 0.50. Also, if each construct's square root of AVE (on the diagonal) exceeds its correlations with other constructs (off-diagonal values), the model is said to have exhibited discriminant validity (Hair et al., 2013). Evidently, Table 3 confirms that each construct is empirically distinct from the others. This is demonstrated by the diagonal values ($\sqrt{AVE}$) of API (.916), PGP (.865), ILR (.887), EXS (.901), and STD (.882), which exceed each construct's corresponding off-diagonal correlation values. This clear variance supports the discriminant validity of the measurement model (outer model).

Table 3. Convergent and Discriminant Validity

Construct	AVE
API	.823
PGP	.789
ILR	.867
EXS	.812
AIA	.742
STD	.796

Table 4 clearly evidenced that the diagonal values (in bold) for each construct: API, PGP, ILR, EXS, and STD are each greater than the corresponding inter-construct correlations, confirming discriminant validity. This further revealed that each of the construct is distinct and valid.

Table 4. Fornell–Larcker criterion (FLC)

Constructs	API	PGP	ILR	EXS	STD
API	.916*				
PGP	.540	.8605*			
ILR	.600	.590	.887*		
EXS	.580	.550	.610	.901*	
STD	.590	.560	.600	.590	.882*

Note. * bolded denotes the $\sqrt{AVE}$ of App Intuitiveness (API), Peer Group Pressure (PGP), Institutional Leadership Readiness (ILR), External Support (EXS), and Student Adaptability (STD)

Structural Equation Model

Having confirmed that the model is both reliable and valid, the next stage is to conduct the structural equation model. Meanwhile, the model was further subjected to goodness of fit (GoF). From Table 5, the Normed Chi-Square (NCS) for the outer (measurement model) stood at 1.651 which conforms to the acceptable values of <3.00 as suggested by Hair et al (2013). However, the structural (inner) model only met the recommended threshold of < 3.00 after its adjustment.

Additionally, the goodness-of-fit indices for the outer (measurement) model: namely the Goodness-of-Fit Index (GFI = 0.915), Adjusted Goodness-of-Fit Index (AGFI = 0.905), Normed Fit Index (NFI = 0.935), Comparative Fit Index (CFI = 0.960), and Tucker-Lewis Index (TLI = 0.950) all met the recommended threshold of ≥ 0.90 , as proposed by Hair et al. (2013) and Arbuckle (1995) all confirmed that the outer model is fit. However, the structural (inner) model only met the recommended threshold of ≥ 0.90 after its adjustment. Similarly, the Root Mean Square Error of Approximation (RMSEA) values for the measurement model (0.035) fall below the acceptable threshold of 0.04 revalidating that the model adequacy. Conversely, the structural (inner) model only met the recommended threshold of < 0.004 after its adjustment.

Table 5. Goodness of Fit and Structural Models

Measures	Acceptable Values	Source	Outer (Measurement) Model	Structural Model	
				Before Adjustment	After Adjustment
NCS	< 3.00	Hair et al (2013)	1.978	3.250	2.010
GFI	≥ 0.90	Hair et al (2013)	0.915	0.855	0.935
AGFI	≥ 0.90	Hair et al (2013)	0.905	0.790	0.925
NFI	≥ 0.90	Arbuckle (1995)	0.935	0.860	0.945
CFI	≥ 0.90	Hair et al (2013)	0.960	0.910	0.975
TLI	≥ 0.90	Hair et al (2013)	0.950	0.895	0.965
RMSEA	< 0.04	Browne and Cudeck (1993)	0.035	0.065	0.038
Model Summary			Accepted	Rejected	Accepted

Note: Normed Chi-Square (NCS); goodness-of-fit index (GFI); adjusted goodness-of-fit index (AGFI); normalized fit index (NFI); Tucker-Lewis index (TLI); comparative fit index; and Root mean square error of approximation (RMSEA)

Hypotheses Testing

Table 6 and Figure 3 present the path relationship among the variables. The three (3) key parameters considered here are Standardized Path Coefficient values (β), the standard error (S.E.) and the t-value. While the β was used to ascertain the direction of relationship of the variables of interest, the t-value was used to test the six (6) hypotheses stated earlier. Consistent with literature, the benchmark t-values for a variable to be statistically significant at the 0.1% (0.001), 1% (0.01), and 5% (0.05) levels (two-tailed test) are approximately ± 3.291 , ± 2.576 , and ± 1.960 , respectively. The structural equation modelling (SEM) served as the main estimation technique used for evaluating the complex relationships among multiple constructs (Hair et al., 2013).

Table 6. Hypotheses Testing Results

Hypothesis	Path Relationships	β	S.E.	t-value	Interpretation
H1	API $\rightarrow$ AIA	0.025	0.017	1.421	Not Supported
H2	PGP $\rightarrow$ AIA	0.270	0.058	4.650***	Supported
H3	ILR $\rightarrow$ AIA	0.212	0.071	2.990**	Supported
H4	EXS $\rightarrow$ AIA	0.090	0.072	1.250	Not Supported
H5	STD $\rightarrow$ AIA	0.185	0.074	2.510**	Supported
H6	AIA $\rightarrow$ STP	0.386	0.069	5.590***	Supported

Note: β denotes Standardized Path Coefficients, S.E. denotes standard errors; * $p < 5\%$; ** $p < .01$; *** $p < 1\%$, Peer Group Pressure (PGP), Institutional Leadership Readiness (ILR), External Support (EXS), and Student Adaptability (STD)

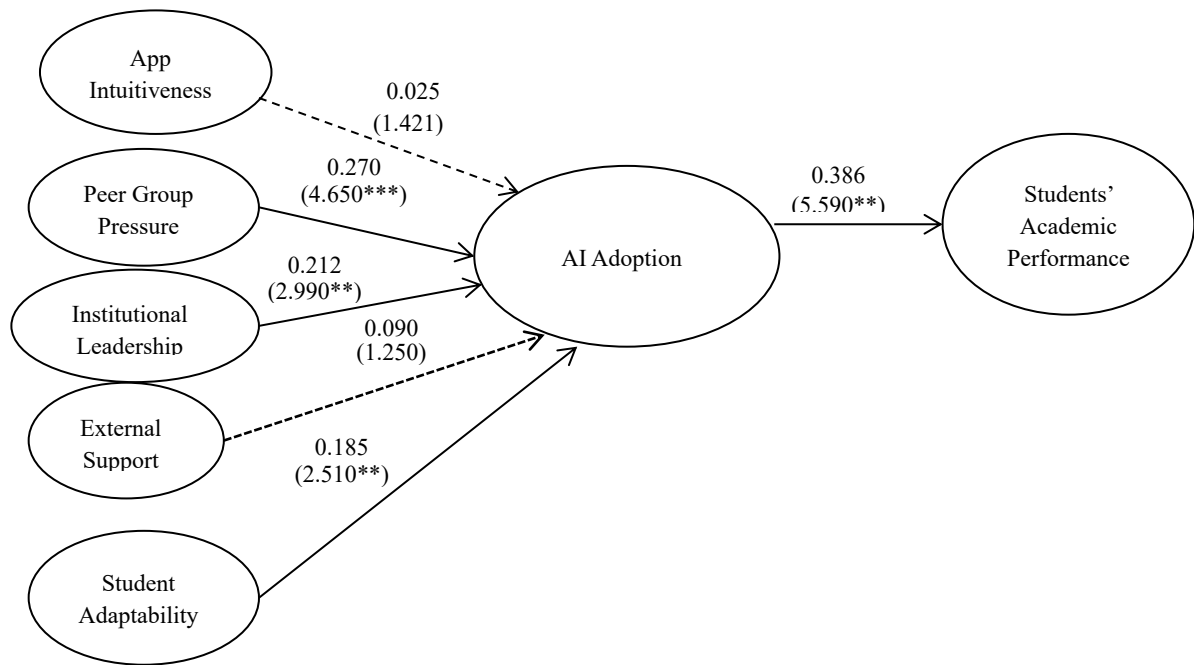


Figure 3. Structural Model Result

Note: Variables with dash denotes no significance while those with straight line denotes significance

6. Discussion of Main Results

This study evaluated the AI adoption drivers and their subsequent impacts on students' academic performance. Drawing insights from the TOE framework, the research empirically evaluated how app intuitiveness, peer influences, institutional leadership readiness, external supports and user adaptability influence students' academic performance. The findings confirmed that both app intuitiveness ($\beta \approx 0.025$ & $t \approx 1.421$) and external support ($\beta \approx 0.090$ & $t \approx 1.250$) failed significantly influence AI adoption. This suggests that though the AI solutions are highly beneficial, most AI solutions are not tailored to meet African educational realities and user needs. Our findings however refute the outcomes of earlier AI drivers studies (Zamani, 2022; Alabdali et al., 2023; Jackson & Allen., 2024; Basit et al, 2024), which confirmed that external supports (third-party supports) and smart technology are critical AI adoption enablers. However, our findings confirmed that the lack of culturally relevant contents and limited external supports appears to have diminished the influence of AI adoption.

Peer group pressure (PGP) has the strongest influence on AI adoption ($\beta \approx 0.270$ & $t \approx 4.650$). This result surpasses the influence of other AI adoption drivers, including institutional leadership readiness ($\beta = 0.212$ & $t \approx 2.990$). Our finding is consistent with prior empirical studies (Korchak et al., 2025; Ramadhan & Usman, 2025;), which reported that students are more inclined to engage with AI-enabled apps when they observe their peers (level mates) are either using or endorsing them. They further confirmed that peer group influence, though it serves as a key driver, is more salient during the initial stage than the later stage of its adoption since most students are still forming judgments about its usage, reliability, and ethical considerations during the initial stage (Ramadhan & Usman, 2025; Vieriu & Petrea, 2025; Zhai et al., 2024; Nguyen & Goto, 2024). Nevertheless, our findings stresses on the need for AI that is built for Africa.

Institutional leadership readiness (ILR) had a strong impact on AI adoption ($\beta \approx 0.212$, $t \approx 2.990$). This construct accounts for the institution's preparedness to invest in digital resources (Jamil et al., 2025; Jan et al., 2024; Lada et al., 2021). The findings revalidate the RBV position that competitive advantage is built in an organization's ability to

mobilize and deploy valuable, rare, inimitable, and non-substitutable (VRIN) resources. In this context, ILR serves as a strategic resource which shapes the organizational climate for innovation and also facilitates the alignment of AI initiatives with university goals. Consistent with prior literature (Jamil et al., 2025; Jan et al., 2024; Lada et al., 2023; Çınar et al., 2021), AI adoption is more likely to succeed in institutions that possess the necessary internal capacities (leadership readiness). These findings highlight the need for DOU management to continue to invest in AI deployment.

Student adaptability (STA) has a positive significant effect on students' academic performance ($\beta \approx 0.185$, $t \approx 2.510$). This suggests that, students' adaptability is a key enhancing AI driver (Ward et al, 2025; Yaseen et al., 2025; Hao et al., 2025). This result aligns with the Human Resource Management (HRM) Theory formulated by Ulrich et al. in 2010. This theory stresses that the three main resource that improve students' performance in technologically savvy environments are agility/readiness, learning orientation and resilience. Consequently, the study underscores that the more educational institutions invest in AI by building a flexible mind-set capable of enabling students navigating an AI-driven academic landscape, the more the extent of AI adoption will increase.

Lastly, AI adoption significantly improves students' academic performance ($\beta \approx 0.386$ and $t \approx 5.590$). This reaffirms that AI has a high strategic educational value. This mirrors extant empirical findings of Badghish and Soomro (2024) & Duan et al. (2019), which confirmed that AI role improves knowledge acquisition, learning efficiency, and academic engagements. Consequently, technological engagement, when complemented with institutional readiness and user needs improve students' performance.

7. Limitations

This research, though, contributes to AI literature in the African context, is faced with several limitations; it suggests the need for future studies. First, the study only sampled accounting, banking and finance students of DOU. Hence, the study is confined to accounting, banking and finance students of DOU only. To cover a wider sample, future research could cut across other institutions of higher learning both in and outside Delta State, Nigeria. Additionally, the study adopted the convenience sampling technique despite the fact that such a sampling technique may result in sampling bias. To overcome this challenge, future studies should use a mixed-method approach. Furthermore, the use of a cross-sectional research design limits insights into long-term adoption trends. To overcome this challenge, future studies should adopt a longitudinal research design since it provides deeper insights into how AI adoption evolves over the years. Lastly, the current study failed to examine the moderating roles of industry-specific challenges, regulatory policies, and ethical considerations on the relationship between AI adoption and students' academic performance. Hence, the study advocates that future researchers should examine the moderating roles of industry-specific challenges, regulatory policies, and ethical considerations on the relationship between AI adoption and students' academic performance.

8. Policy Implications

The research offers remarkable contributions to behavioural science research on the effect of AI adoption on the performance of students in the Nigerian education sector. First, the research provides insights on the various psychological, organisational and social factors influencing AI adoption in the African context by drawing inference from the Technological Acceptance Model (TAM) and the Resource-Based View (RBV). The research reported that organisational readiness and institutional leadership commitment both improve students' academic performance. This result validates the TAM, which stressed that perceived ease of use and perceived usefulness determine individuals' acceptance of AI adoption (Davis, 1989). This further reinforces the view that leadership behaviour and institutional culture are major factors which drive technology adoption in the educational settings (Feng et al., 2025).

Furthermore, the study reported that peer group pressure (ethical use of AI) improves students' academic performance, highlighting the critical roles of collaborative learning environments in shaping technological acceptance. Justifiably, this result validates the behavioural science notion which states that social influences and environmental stimuli both interact with individual (students, in this case) and organisational decision-making processes (DOU, in this case) to determine technology adoption. Similarly, the result confirmed that increased levels of AI adoption improve students' academic performance. This emphasizes that technological adoption play high transformative roles in improving students' learning outcomes.

Additionally, the research deepens the management science research by adding institutional-level resources and preparedness, highlighting that organisational readiness, rather than students' perceptions only, plays a significant role in aiding AI adoption. Lastly, the findings confirmed that leadership commitment influences AI adoption more than students' adaptability, highlighting that institutional efforts and leadership support outweigh individual traits in driving AI integration.

9. Conclusion

This study evaluate whether technological factors (app intuitiveness and peer group pressure), organisational factors (institutional leadership commitment and organisational readiness), environmental factors (external support), and individual-level factors (students adaptability) individually influence AI adoption. Also, emphasis was placed on how these AI adoption drivers influence students' academic performance. The findings highlight peer group pressure,

institutional leadership commitment and organisational readiness, as well as students' adaptability, influencing AI adoption significantly. However, the levels of influence of app intuitiveness and external support are still very low. This suggests that most of the AI applications are yet to fully meet both user needs and local content. Similarly, AI adoption significantly positively affects students' academic performance. In the light of this, various actionable recommendations are made. To increase the rate of AI adoption in the African context, AI developers must develop intuitive apps tailored to the African educational realities. This requires that AI applications be designed with content that reflects the African learning needs, cultural contexts, and local languages. Although external support was recorded as not a major AI adoption driver, the current content and infrastructure gaps can be addressed through strategic stakeholder engagement between technology providers and educational partners.

Furthermore, DOU management need to organise trainings on AI competencies and digital literacy for both students and staff regularly. Also, they need to strengthen their level commitment to AI adoption through strategic planning, optimal resource allocation, and the development of actionable policies on the ethical use of AI. To further deepen AI adoption in the African university context, Nigerian Universities need to give grants should to Nigerian scholars conducting AI researches. Lastly, DOU management team needs to implement peer-led digital literacy programs and must ensure that ethical use of AI is entrenched in Students' Handbook.

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Authors contributions

Judith, O. PATRICK: conceptualized the study and drafted the initial manuscript; Bashiru UMORU: conducted a systematic literature review, Theresa Nkechi OFOR: handled the methodology, Juliet Chinyere OBI: designed the questionnaire; Jennifer Chigozie OKAFOR: did the discussion of findings; & Oghenekparobo Ernest AGBOGUN: shared the questionnaire, edited the manuscript and served as the corresponding author. All authors read and approved the final manuscript.

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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 countermeasures. *Advances in Mobile Learning Educational Research*, 4(2), 1149-1159. <https://doi.org/10.25082/AMLER.2024.02.009>
- Adewale, M. D., Azeta, A., Abayomi-Alli, A., & Sambo-Magaji, A. (2024). Impact of artificial intelligence adoption on students' academic performance in open and distance learning: A systematic literature review. *Heliyon*. <https://doi.org/10.1016/j.heliyon.2024.e40025>
- Ahmad, S. F., Rahmat, M. K., Mubarik, M. S., Alam, M. M., & Hyder, S. I. (2021). Artificial intelligence and its role in education. *Sustainability*, 13(22), 12902. <https://doi.org/10.3390/su132212902>
- Ajagunna, A. E., & Isaruk, I. O. E. D. (2022). The Influence of Educational Mobile Apps Use on Teaching Effectiveness of Lecturers in Public Polytechnics in Ekiti and Ondo states, Nigeria. *International Journal of Research and Innovation in Social Science*, 6(7), 26-33. https://econpapers.repec.org/article/bcpjournal/v_3a6_3ay_3a2022_3ai_3a7_3ap_3a26-33.htm
- Alabdali, S. A., Pileggi, S. F., & Cetindamar, D. (2023). Influential factors, enablers, and barriers to adopting smart technology in rural regions: A literature review. *Sustainability*, 15(10), 7908. <https://doi.org/10.3390/su15107908>
- Alneyadi, S., Wardat, Y., Alshannag, Q., & Abu-Al-Aish, A. (2023). The effect of using smart e-learning app on the academic achievement of eighth-grade students. *Eurasia Journal of Mathematics, Science and Technology Education*, 19(4), em2248. <https://doi.org/10.29333/ejmste/13067>
- Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *PACIS*, 4, 231–245. Available online: <https://core.ac.uk/download/pdf/301376079.pdf>
- Baashar, Y., Hamed, Y., Alkaws, G., Capretz, L. F., Alhussian, H., Alwadain, A., & Al-amri, R. (2022). Evaluation of postgraduate academic performance using artificial intelligence models. *Alexandria Engineering Journal*, 61(12), 9867-9878. <https://doi.org/10.1016/j.aej.2022.03.021>
- Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: application of technology–organization–environment framework. *Sustainability*, 16(5), 1864. <https://doi.org/10.3390/su16051864>
- Bali, B., Garba, E. J., Ahmadu, A. S., Takwate, K. T., & Malgwi, Y. M. (2024). Analysis of emerging trends in artificial intelligence for education in Nigeria. *Discover Artificial Intelligence*, 4(1), 110. <https://doi.org/10.1007/s44163-024-00163-y>
- Basit, S. A., Gharleghi, B., Batool, K., Hassan, S. S., Jahanshahi, A. A., & Kliem, M. E. (2024). Review of enablers and barriers of sustainable business practices in SMEs. *Journal of Economy and Technology*, 2, 79-94. <https://doi.org/10.1016/j.ject.2024.03.005>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *Ieee Access*, 8, 75264-75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Chen, Y., Yin, Y., Browne, G. J., & Li, D. (2019). Adoption of building information modeling in Chinese construction industry: The technology-organization-environment framework. *Engineering, Construction and Architectural Management*, 26(9), 1878-1898. <https://doi.org/10.1108/ECAM-11-2017-0246>
- Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society*, 62, 101257. <https://doi.org/10.1016/j.techsoc.2020.101257>
- Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, 205(219), 5. <https://quod.lib.umich.edu/b/busadwp/images/b/1/4/b1409190.0001.001.pdf>
- Demir, B. T., Eşme, S., Patat, D., & Bilecenoğlu, B. (2023). The effect of mobile applied anatomy learning on students' academic success, cognitive loads, and attitudes. *Medical Science Educator*, 33(3), 711-718. <https://doi.org/10.1007/s40670-023-01787-y>
- Demir, K., & Akpinar, E. (2018). The Effect of Mobile Learning Applications on Students' Academic Achievement and Attitudes toward Mobile Learning. *Malaysian Online Journal of Educational Technology*, 6(2), 48-59. <https://doi.org/10.17220/mojet.2018.02.004>
- Felemban, H., Sohail, M., & Ruikar, K. (2024). Exploring the readiness of organisations to adopt artificial intelligence. *Buildings*, 14(8), 2460. <https://doi.org/10.3390/buildings14082460>
- Feng, J., Yu, B., Tan, W. H., Dai, Z., & Li, Z. (2025). Key factors influencing educational technology adoption in higher

- education: A systematic review. *PLOS Digital Health*, 4(4), e0000764. <https://doi.org/10.1371/journal.pdig.0000764>
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning*, 46(1-2), 1-12. <https://doi.org/10.1016/j.lrp.2013.01.001>
- Jackson, D., & Allen, C. (2024). Enablers, barriers and strategies for adopting new technology in accounting. *International Journal of Accounting Information Systems*, 52, Article 100666. <https://doi.org/10.1016/j.accinf.2023.100666>
- Jamil, K., Zhang, W., Anwar, A., & Mustafa, S. (2025). Exploring the Influence of AI Adoption and Technological Readiness on Sustainable Performance in Pakistani Export Sector Manufacturing Small and Medium-Sized Enterprises. *Sustainability*, 17(8), 3599. <https://doi.org/10.3390/su17083599>
- Jan, S. U., Khan, M. S. A., & Khan, A. S. (2024). Organizational readiness to adopt artificial intelligence in the library and information sector of Pakistan. *Evidence Based Library and Information Practice*, 19(1), 58-76. <https://doi.org/10.18438/ebliip30408>
- Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective. *Intelligent Systems in Accounting, Finance and Management*, 28(4), 217-238. <https://doi.org/10.1002/isaf.1503>
- Khasawneh, M. A. S., & Khasawneh, Y. J. A. (2023). Analyzing the Effectiveness of Mobile Devices and Apps in Supporting Learning. *Migration Letters*, 20(1), 901-10. https://www.researchgate.net/profile/Yusra-Khasawneh/publication/375693035_Migration_Letters_Analyzing_the_Effectiveness_of_Mobile_Devices_and_Apps_in_Supporting_Learning/links/65567e8f3fa26f66f40742a3/Migration-Letters-Analyzing-the-Effectiveness-of-Mobile-Devices-and-Apps-in-Supporting-Learning.pdf
- Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology*, 45(3), 298-311. <https://doi.org/10.1080/17439884.2020.1754236>
- Koohestani, H. R., Arabshahi, S. K. S., Fata, L., & Ahmadi, F. (2018). The educational effects of mobile learning on students of medical sciences: A systematic review in experimental studies. *Journal of advances in medical education & professionalism*, 6(2), 58. <https://doi.org/10.1080/14703297.2025.2496942>
- Korchak, A., Al Murshidi, G., Getman, A., Raouf, N., Arshe, M., Al Meheiri, N., ... & Costley, J. (2025). The role of social influence in generative artificial intelligence ChatGPT adoption intentions among undergraduate and graduate students. *Innovations in Education and Teaching International*, 1-15. <https://doi.org/10.1016/j.joitmc.2023.100144>
- Lada, S., Chekima, B., Karim, M. R. A., Fabeil, N. F., Ayub, M. S., Amirul, S. M., ... & Zaki, H. O. (2023). Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4), Article 100144. <https://doi.org/10.1016/j.joitmc.2023.100144>
- Najdawi, A. (2020). Assessing AI readiness across organizations: The case of UAE. In *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)* (pp. 1-5). IEEE. <https://doi.org/10.1109/ICCCNT49239.2020.9225386>
- Ngonso, B., Egielewa, P., Egenti, G., Uduehi, I., Sunny-Duke, F., Ukhurebor, K., ... & Osemengbe, U. (2025). Influence of artificial intelligence on educational performance of Nigerian students in tertiary institutions in Nigeria. *Journal of Infrastructure, Policy and Development*, 9(1), 9949. <https://doi.org/10.24294/jipd9949>
- Nguyen, H. M., & Goto, D. (2024). Unmasking academic cheating behavior in the artificial intelligence era: Evidence from Vietnamese undergraduates. *Education and Information Technologies*, 29(12), 15999-16025. <https://doi.org/10.1007/s10639-024-12495-4>
- Obomeghie, M. A. (2025). Artificial intelligence and students entrepreneurship achievements in Nigeria. *ISA Journal of Business, Economics and Management (ISAJBEM)*, 2(3), 170-181. <https://doi.org/10.5281/zenodo.15433830>
- Panigrahi, D. A. K. (2020). Use of artificial intelligence in education. *Management Accountant*, 55, 64-67. <https://doi.org/10.33516/maj.v55i5.64-67p>
- Ramadhan, Z., & Usman, O. (2025). Technology Adoption and Peer Influence on Student AI Research Tools Purchase Intention. *International Student Conference on Business, Education, Economics, Accounting, and Management (ISC-BEAM)*, 3(1), 852-871. <https://doi.org/10.21009/ISC-BEAM.013.59>
- Razak, A., Nayak, M. P., Manoharan, G., Durai, S., Rajesh, G. A., Rao, C. B., & Ashtikar, S. P. (2023). Reigniting the

- power of artificial intelligence in education sector for the educators and students competence. In *Artificial Intelligence and Machine Learning in Smart City Planning* (pp. 103-116). Elsevier. <https://doi.org/10.1016/B978-0-323-99503-0.00009-0>
- Shang, G., Low, S. P., & Lim, X. Y. V. (2023). Prospects, drivers of and barriers to artificial intelligence adoption in project management. *Built Environment Project and Asset Management*, 13(5), 629-645. <https://doi.org/10.1108/BEPAM-12-2022-0195>
- Soomro, Y. A., Ali, M., Yaqub, M. Z., Ali, I., & Badghish, S. (2024). Financial education is more precious than money-examining the role of financial literacy in enhancing financial wellbeing among Saudi women. *International Journal of Business Performance Management*, 25(1), 1-24. <https://doi.org/10.1504/IJBPM.2024.135155>
- Ulrich, C. M., Taylor, C., Soeken, K., O'Donnell, P., Farrar, A., Danis, M., & Grady, C. (2010). Everyday ethics: ethical issues and stress in nursing practice. *Journal of advanced nursing*, 66(11), 2510-2519. <https://doi.org/10.1111/j.1365-2648.2010.05425.x>
- Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68, 102588. <https://doi.org/10.1016/j.ijinfomgt.2022.102588>
- Uriri, C., & Mmom, C. P. (2025). Integration of Artificial Intelligence in Educational Leadership for Sustainable Development in Nigeria. *International Journal of Educational Management, Rivers State University*, 1(1), 209-220. <https://ijedm.com/index.php/ijedm/article/view/19>
- Vieriu, A. M., & Petrea, G. (2025). The impact of artificial intelligence (AI) on students' academic development. *Education Sciences*, 15(3), 343. <https://doi.org/10.3390/educsci15030343>
- Vongurai, R. (2025). Examining Organizational and Human Drivers of Artificial Intelligence Adoption for Enhancing Operational Performance in Thai Technology Enterprises. *The Journal of Behavioral Science*, 20(2), 1-14. <https://doi.org/10.69523/tjbs.2025.282283>
- Zamani, S. Z. (2022). Small and Medium Enterprises (SMEs) facing an evolving technological era: a systematic literature review on the adoption of technologies in SMEs. *European Journal of Innovation Management*, 25(6), 735-757. <https://doi.org/10.1108/EJIM-07-2021-0360>
- Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. *Smart Learning Environments*, 11(1), 28. <https://doi.org/10.1186/s40561-024-00316-7>