LEARNING MANAGEMENT SYSTEM USE, AI-ENABLED INSTRUCTIONAL TOOLS, AND DIGITAL INFRASTRUCTURE QUALITY ON STUDENT LEARNING OUTCOMES IN HIGHER EDUCATION

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Abstract

This study examined the predictive relationships among Learning Management System (LMS) usage, artificial intelligence (AI)-enabled instructional tools, digital infrastructure quality, and student learning outcomes in higher education institutions in the South-South geopolitical zone of Nigeria. A descriptive correlational research design was adopted for the study. The population consisted of 23,810 undergraduate students from eight federal universities, while a sample of 1,384 students was selected using multi-stage sampling techniques. Data were collected using a structured questionnaire titled Learning Management System Use, AI-Enabled Instructional Tools, Digital Infrastructure Quality and Student Learning Outcomes Questionnaire (LAID-SLOQ). *The instrument had a reliability coefficient of 0.79 determined using Cronbach's Alpha. Data were analyzed using mean, standard deviation, simple regression, and multiple regression analysis at a 0.05 level of significance. The findings revealed that LMS usage, AI-enabled instructional tools, and digital infrastructure quality each significantly predicted student learning outcomes. The results further showed that the three variables jointly made a significant contribution to student learning outcomes, with AI-enabled instructional tools making the strongest individual contribution. The study concluded that effective technology integration supported by adequate digital infrastructure significantly improves student learning outcomes in higher education. It was recommended that universities strengthen digital infrastructure, promote effective LMS integration, and support the adoption of AI-enabled instructional tools in teaching and learning.*

Keywords*:* learning management system, ai-enabled instructional tools, digital infrastructure quality, student learning outcomes, higher education, south-south Nigeria

Introduction

With the growing adoption of digital technologies in higher education, many institutions still struggle to improve student learning outcomes in technology mediated learning environments. The presence of Learning Management Systems, artificial intelligence enabled instructional tools, and digital infrastructure does not automatically lead to effective learning or academic success. Research indicates that the educational value of technology depends largely on how it is integrated into teaching practice rather than on its availability alone (Bates, 2024; Kirkwood & Price, 2014; Selwyn, 2016). In many universities in developing countries, inconsistent LMS use, limited integration of AI instructional tools, and inadequate digital infrastructure create uneven learning experiences among students. These conditions often widen existing gaps in access to quality learning opportunities. For this reason, careful examination of institutional practices, technological readiness, and user competence remains important for improving student learning outcomes in higher education.

The integration of digital technologies into higher education has changed how teaching and learning are designed, delivered, and evaluated across universities. Many institutions rely on Learning Management Systems to organise course materials, manage assessment activities, and support communication between lecturers and students (McCarthy & Palmer, 2023; Turnbull et al., 2021). These systems support blended and online learning by improving access to instructional resources and collaborative activities. However, the educational benefits of LMS platforms depend on how lecturers and students use them in teaching and learning processes. Research indicates that LMS platforms are often used mainly for storing materials rather than supporting interactive learning activities (Al-Fraihat et al., 2020; Fathema et al., 2020; Johnson et al., 2016). Limited instructional use reduces their contribution to student engagement and academic achievement. In addition, understanding patterns of LMS adoption remains important for evaluating their role in improving student learning outcomes.

Artificial intelligence enabled instructional tools are becoming important components of modern teaching and learning in higher education. Technologies such as adaptive learning systems, automated feedback tools, and intelligent tutoring systems support personalised learning and data informed instructional decisions (Holmes et al., 2019; Luckin et al., 2016). These tools help identify learning gaps and support students through customised learning pathways and timely feedback (Zawacki-Richter et al., 2019). However, their effectiveness depends on institutional preparedness, digital literacy of lecturers and students, and access to technological resources (Bond et al., 2021; Khosravi et al., 2022). Without adequate training and technical support, universities may not fully benefit from AI enabled instructional tools. Evaluating how these technologies are integrated into teaching practice remains essential for improving learning outcomes in higher education.

Digital infrastructure quality also plays an important role in technology supported learning. Reliable internet connectivity, access to digital devices, stable electricity supply, and institutional technical support systems provide the foundation for effective digital learning implementation (Czerniewicz et al., 2020; UNESCO, 2021 as cited by Carney, 2022). Where these facilities are limited or inconsistent, students face barriers that reduce participation in digital learning activities (Adarkwah, 2021; Dhawan, 2020). These challenges remain common in many developing countries, where unequal access to digital resources continues to affect higher education delivery. In addition, infrastructure limitations reduce student engagement and academic performance in technology mediated learning environments. For this reason, examining the combined influence of LMS use, AI-enabled instructional tools, and digital infrastructure quality is necessary to understand how digital learning environments can improve student learning outcomes in higher education (Bates, 2024).

Literature Review

Learning Management System Usage and Student Learning Outcomes

The Technology Acceptance Model, proposed by Davis in 1989, provides a useful theoretical basis for explaining Learning Management System usage in higher education. The model states that perceived usefulness and perceived ease of use influence an individual's intention to adopt and use a technology. When students perceive an LMS as useful for improving academic performance and easy to navigate, they are more likely to engage actively with it. This theory is relevant to the relationship between LMS usage and student learning outcomes because sustained and meaningful use of the platform depends on student beliefs about its value for learning. If students consider the LMS beneficial for accessing materials, submitting

assignments, and interacting with lecturers, engagement may increase and positively influence academic performance.
Empirical evidence indicates that effective LMS usage is associated with improved student learning outcomes. Turnbull et al. (2021) found that meaningful engagement with LMS platforms improves the quality of learning experiences and academic participation. Fathema (2023) reported that the instructional strategies adopted by lecturers determine whether LMS platforms support deep learning or remain limited to administrative functions. Al-Fraihat et al. (2020) observed that system quality, information quality, and service quality significantly influence student satisfaction and academic performance. In addition, McCarthy and Palmer (2023) argued that LMS supported blended learning environments improve interaction and collaborative knowledge construction. Johnson et al. (2016) further noted that institutions that integrate LMS tools into assessment and feedback processes record better learning outcomes. However, where LMS use is inconsistent or poorly managed, the impact on student performance remains limited. These findings suggest that the predictive strength of LMS usage depends on depth of integration, instructional design, and institutional support.

Artificial Intelligence Enabled Instructional Tools and Student Learning Outcomes
The Cognitive Theory of Multimedia Learning, proposed by Mayer in 2001, explains how learners process information through verbal and visual channels. The theory states that learning improves when instructional materials are designed in line with human cognitive architecture and when cognitive overload is minimized. Artificial intelligence enabled instructional tools such as adaptive learning systems and intelligent tutoring systems can personalize instruction and adjust content based on learner progress. This theoretical position is relevant because AI tools can tailor feedback, pacing, and instructional materials to individual learner needs, thereby supporting improved comprehension and retention. When properly implemented, such tools may strengthen the relationship between instructional support and student learning outcomes.

Empirical studies indicate that artificial intelligence enabled instructional tools can positively influence student learning outcomes in higher education. Zawacki Richter et al. (2019) reported that AI applications in higher education improve personalized learning and academic achievement. Luckin et al. (2016) explained that intelligent tutoring systems provide immediate feedback and adaptive guidance, which enhance student performance. Holmes et al. (2019) noted that AI systems support early identification of learning difficulties and assist lecturers in making data informed decisions. Bond et al. (2021) observed that digital competence and institutional readiness determine the success of technology supported learning initiatives. Chukwu et al. (2026) and Khosravi et al. (2022) added that effective integration of AI tools into pedagogy improves student engagement and assessment practices. However, limited technical capacity and inadequate training may reduce their educational value. The empirical literature therefore suggests that AI enabled instructional tools can significantly predict student learning outcomes when supported by sound pedagogy and adequate infrastructure.

Digital Infrastructure Quality and Student Learning Outcomes
The Diffusion of Innovations Theory, proposed by Rogers et al. (2014) explains how new technologies are adopted within social systems. The theory states that adoption depends on perceived advantage, compatibility, complexity, trialability, and observability. Digital infrastructure quality, including reliable internet connectivity, access to digital devices, and stable electricity supply, influences the rate and effectiveness of technology adoption in higher education institutions. When infrastructure is reliable and accessible, students and

lecturers can consistently engage with digital learning tools. This theoretical perspective is relevant because inadequate infrastructure may limit the effective use of educational technologies and weaken their influence on student learning outcomes.

Empirical research confirms that digital infrastructure quality significantly affects student learning outcomes. Czerniewicz et al. (2020) reported that unequal access to internet connectivity and digital devices during emergency remote teaching reduced student participation and academic success. Dhawan (2020) explained that stable connectivity and institutional technical support are essential for effective online learning delivery. Adarkwah (2021) found that infrastructure limitations in developing countries restricted student engagement with online platforms. UNESCO (2021) as cited by Carney (2022) emphasized that digital inequality continues to affect higher education systems globally, particularly in low resource environments. Bates (2024) argued that investments in digital infrastructure must accompany pedagogical reform to improve learning outcomes. These empirical findings indicate that without adequate infrastructure, the potential benefits of LMS platforms and AI enabled instructional tools may not translate into improved academic performance. Digital infrastructure quality, therefore, remains a critical predictor of student learning outcomes in technology mediated higher education environments.

Methodology

The study adopted a descriptive correlational research design to examine the predictive relationships among Learning Management System (LMS) use, AI-enabled instructional tools, digital infrastructure quality, and student learning outcomes in federal universities in the South-South geopolitical zone of Nigeria. The population of the study comprised 23,810 undergraduate students drawn from eight federal universities in South-South Nigeria during the 2024/2025 academic session. A sample size of 1,384 undergraduate students was determined using the Krejcie and Morgan sample size table and selected through a multi-stage sampling procedure involving stratified sampling to group the universities, proportionate sampling to allocate respondents according to institutional population size, and simple random sampling to select students within faculties. Data were collected using a structured questionnaire titled Learning Management System Use, AI-Enabled Instructional Tools, Digital Infrastructure Quality and Student Learning Outcomes Questionnaire (LAID-SLOQ). The instrument contained five sections with a total of 45 items: Section A (Demographic Information) contained 5 items, Section B (LMS Use Scale) contained 12 items, Section C (AI-Enabled Instructional Tools Scale) contained 10 items, Section D (Digital Infrastructure Quality Scale) contained 8 items, and Section E (Student Learning Outcomes Scale) contained 10 items. The instrument was structured on a four-point Likert scale of Strongly Agree (4), Agree (3), Disagree (2), and Strongly Disagree (1). Face and content validity of the instrument were established by five experts in Educational Technology and Measurement and Evaluation, while reliability was determined through a pilot study using students outside the study area, yielding a Cronbach's Alpha reliability index of 0.79, indicating high internal consistency. Permission to conduct the study was obtained from the relevant university authorities, after which the researcher, assisted by trained research assistants, administered the questionnaire through both physical distribution and online forms. Respondents were informed about the purpose of the study and assured of confidentiality and voluntary participation. The data collected were coded and analyzed using the Statistical Package for Social Sciences (SPSS) version 28. Mean and standard deviation were used to answer the research questions, while multiple regression analysis was used to test the three null hypotheses at the 0.05 level of significance in order to determine the individual and combined predictive contributions of LMS use, AI-enabled instructional tools, and digital infrastructure quality to student learning outcomes in higher education.

Objectives of the Study

1. To determine the extent to which Learning Management System usage predicts student learning outcomes in higher education institutions.
2. To examine the extent to which artificial intelligence enabled instructional tools predict student learning outcomes in higher education institutions.
3. To determine the extent to which digital infrastructure quality predicts student learning outcomes in higher education institutions.

Research Questions

1. To what extent does Learning Management System usage predict student learning outcomes in higher education institutions?
2. To what extent do artificial intelligence enabled instructional tools predict student learning outcomes in higher education institutions?
3. To what extent does digital infrastructure quality predict student learning outcomes in higher education institutions?

Hypotheses

1. Learning Management System usage does not significantly predict student learning outcomes in higher education institutions.
2. Artificial intelligence enabled instructional tools do not significantly predict student learning outcomes in higher education institutions.
3. Digital infrastructure quality does not significantly predict student learning outcomes in higher education institutions.

Results

Hypothesis One

Learning Management System usage does not significantly predict student learning outcomes in higher education institutions.

The independent variable in this hypothesis is Learning Management System usage, while the dependent variable is student learning outcomes. Simple linear regression analysis was employed to test this hypothesis. The result of the analysis is presented in Table 1.

The result of simple regression analysis in Table 1 on the relationship between Learning Management System usage and student learning outcomes in higher education institutions produced an adjusted R^2 of .505. This result implies that 50.5 percent of the variance in student learning outcomes can be predicted from the independent variable (Learning Management System usage) in higher education institutions. The F-value of the Analysis of Variance (ANOVA) obtained from the regression table was F = 1411.442, having a p-value of .000 with 1 and 1382 degrees of freedom at .05 level of significance. The null hypothesis was rejected. This result therefore signifies that Learning Management System usage significantly predicted student learning outcomes in higher education institutions by 50.5 percent, and the identified equation to understand this relationship was:

Student learning outcomes = 14.118 + 0.844 (Learning Management System usage).

Table 1: ***Table Showing Simple Regression Analysis of the Relationship Between Learning Management System Usage and Student Learning Outcomes in Higher Education Institutions***

Model	Sum of Squares	DF	Mean Square	F	Sig
Regression	28059.284	1	28059.284	1411.442	.000
Residual	27473.973	1382	19.880		
Total	55533.257	1383			

Unstandardized Coefficients		Standardized Coefficients	T	Sig.
B	Std. Error	Beta		
(Constant)	14.118	.386		36.532
Learning Management System usage	.844	.022	.711	37.569

$P < .05$
$R = .711$
R Square = .505
Adjusted R Square = .505
Predictors: (Constant), Learning Management System usage
Dependent Variable: Student learning outcomes in higher education institutions

Hypothesis Two
Artificial intelligence enabled instructional tools do not significantly predict student learning outcomes in higher education institutions.

The independent variable in this hypothesis is Artificial intelligence-enabled instructional tools, while the dependent variable is student learning outcomes. Simple linear regression analysis was employed to test this hypothesis. The result of the analysis is presented in Table 2.

The result of simple regression analysis in Table 2 on the relationship between artificial intelligence-enabled instructional tools and student learning outcomes in higher education institutions produced an adjusted R^2 of .529. This result implies that 52.9 percent of the variance in student learning outcomes can be predicted from the independent variable (artificial intelligence - enabled instructional tools) in higher education institutions. The F-value of the Analysis of Variance (ANOVA) obtained from the regression table was F = 1555.498, having a p-value of .000 with 1 and 1382 degrees of freedom at .05 level of significance. The null hypothesis was rejected. This result therefore signifies that artificial intelligence-enabled instructional tools significantly predicted student learning outcomes in higher education institutions by 52.9 percent, and the identified equation to understand this relationship was:
Student learning outcomes = 14.327 + 0.862 (Artificial intelligence-enabled instructional tools).

Table 2: ***Table Showing Simple Regression Analysis of the Relationship Between Artificial Intelligence-Enabled Instructional Tools and Student Learning Outcomes in Higher Education Institutions***

Model	Sum of Squares	DF	Mean Square	F	Sig
Regression	29406.618	1	29406.618	1555.498	.000
Residual	26126.639	1382	18.905		
Total	55533.257	1383			

Unstandardized Coefficients		Standardized Coefficients	t	Sig.
B	Std. Error	Beta		
(Constant)	14.327	.364		39.364
Artificial intelligence-enabled instructional tools	.862	.022	.728	39.440

P < .05
R = .728
R Square = .530
Adjusted R Square = .529
Predictors: (Constant), Artificial intelligence-enabled instructional tools
Dependent Variable: Student learning outcomes in higher education institutions

Hypothesis Three

Digital infrastructure quality does not significantly predict student learning outcomes in higher education institutions. The independent variable in this hypothesis is digital infrastructure quality, while the dependent variable is student learning outcomes. Simple linear regression analysis was employed to test this hypothesis. The result of the analysis is presented in Table 3.

The result of simple regression analysis in Table 3 on the relationship between digital infrastructure quality and student learning outcomes in higher education institutions produced an adjusted R^2 of .527. This result implies that 52.7 percent of the variance in student learning outcomes can be predicted from the independent variable (digital infrastructure quality) in higher education institutions. The F-value of the Analysis of Variance (ANOVA) obtained from the regression table was F = 1542.970, having a p-value of .000 with 1 and 1382 degrees of freedom at .05 level of significance. The null hypothesis was rejected. This result therefore signifies that digital infrastructure quality significantly predicted student learning outcomes in higher education institutions by 52.7 percent, and the identified equation to understand this relationship was:
Student learning outcomes = 13.659 + 0.860 (Digital infrastructure quality).

Table 3: ***Table Showing the Simple Regression Analysis of the Relationship Between Digital Infrastructure Quality and Student Learning Outcomes in Higher Education Institutions***

Model	Sum of Square	DF	Mean Square	F	Sig
Regression	29294.708	1	29294.708	1542.970	.000
Residual	26238.549	1382	18.986		
Total	55533.257	1383			

Unstandardized Coefficients		Standardized Coefficients	t	Sig.
B	Std. Error	Beta		
(Constant)	13.659	.381		35.805
Digital infrastructure quality	.860	.022	.726	39.281

P < .05
R = .726
R Square = .528

Adjusted R Square = .527
Predictors: (Constant), Digital infrastructure quality
Dependent Variable: Student learning outcomes in higher education institutions

Hypothesis Four
Learning Management System usage, artificial intelligence enabled instructional tools and digital infrastructure quality do not jointly predict student learning outcomes in higher education institutions

The independent variables in this hypothesis are Learning Management System (LMS) usage, artificial intelligence enabled instructional tools, and digital infrastructure quality, while the dependent variable is student learning outcomes in higher education institutions. Simultaneous multiple regression analysis was employed to test this hypothesis, and the result of the analysis is presented in Table 4.

The multiple regression analysis in Table 4 examining the independent and joint contributions of Learning Management System usage, artificial intelligence enabled instructional tools, and digital infrastructure quality to student learning outcomes produced an adjusted R^2 of .619. This result indicates that 61.9% of the variance in student learning outcomes can be explained by the combined influence of LMS usage, AI-enabled instructional tools, and digital infrastructure quality. The Analysis of Variance (ANOVA) result yielded an F-value of 749.630 with 3 and 1,380 degrees of freedom at the .05 level of significance ($p = .000$). Based on this result, the null hypothesis was rejected, indicating that the independent variables jointly and significantly predict student learning outcomes in higher education institutions.

Table 4 further showed that the combination of the three predictor variables yielded a multiple correlation coefficient (R) of .787 and an R-square value of .620, confirming a strong joint relationship between the predictors and student learning outcomes. The adjusted R-square of .619 implies that the regression model explains 61.9% of the variance in student learning outcomes, while the remaining 38.1% may be attributed to other factors not included in the model. The significant F-ratio confirms that the regression model provides a good fit for predicting student learning outcomes.

To determine the relative contributions of the individual predictors, the regression weights were examined. The standardized beta coefficients ranged from .182 to .358, while the t-values ranged from 5.807 to 13.359, all significant at the .05 level. The results showed that artificial intelligence enabled instructional tools ($\beta = .358$, $t = 13.359$) made the greatest contribution to student learning outcomes, followed by digital infrastructure quality ($\beta = .317$, $t = 10.626$), and Learning Management System usage ($\beta = .182$, $t = 5.807$). All three predictors were statistically significant, indicating that each variable independently and jointly contributes to student learning outcomes.

The regression equation describing the relationship is expressed as:
Student Learning Outcomes = 11.485 + 0.216 (LMS Usage) + 0.424 (AI-Enabled Instructional Tools) + 0.376 (Digital Infrastructure Quality)

Table 4: ***Table Showing the Multiple Regression Analysis Showing the Joint Prediction of Learning Management System Usage, Artificial Intelligence Enabled Instructional Tools,***

and Digital Infrastructure Quality on Student Learning Outcomes in Higher Education Institutions

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	34,414.976	3	11,471.659	749.630	.000
Residual	21,118.281	1,380	15.303		
Total	55,533.257	1,383			

Variables	B	Std. Error	Beta	T	Sig.
Constant	11.485	.363		31.610	.000
Learning Management System usage	.216	.037	.182	5.807	.000
Artificial intelligence enabled instructional tools	.424	.032	.358	13.359	.000
Digital infrastructure quality	.376	.035	.317	10.626	.000

$P < .05$
$R = .787$
R Square = .620
Adjusted R Square = .619
Predictors: (Constant), Digital infrastructure quality, Artificial intelligence enabled instructional tools, Learning Management System usage
Dependent Variable: Student learning outcomes in higher education institutions

Discussion of Findings

The findings of the study showed that Learning Management System (LMS) usage significantly predicted student learning outcomes in higher education institutions. This indicates that increased engagement with LMS platforms contributes positively to students' academic performance and learning experiences. This finding agrees with studies by Turnbull et al. (2021), Al-Fraihat et al. (2020), Johnson et al. (2016), and McCarthy and Palmer (2023), who reported that LMS-supported learning environments improve access to instructional resources, feedback processes, collaboration, and academic engagement, ultimately enhancing learning outcomes. Similarly, Fathema (2023) emphasized that effective instructional use of LMS platforms improves learning quality. However, the finding contrasts with studies suggesting that LMS platforms sometimes have minimal impact on academic performance when used primarily for administrative purposes or when students lack digital engagement skills. What is particularly significant about this finding is the relatively strong predictive contribution of LMS usage to student learning outcomes, suggesting that LMS platforms are no longer merely supplementary tools but central components of teaching and learning in higher education.

The study revealed that artificial intelligence enabled instructional tools significantly predicted student learning outcomes in higher education institutions. This suggests that AI-supported instructional systems, such as adaptive learning platforms and intelligent feedback tools, enhance students' understanding, engagement, and academic achievement. This finding is consistent with the work of Zawacki-Richter et al. (2019), Luckin et al. (2016), Holmes et al. (2019), Bond et al. (2021), Khosravi et al. (2022), and Chukwu et al. (2026), who reported that AI technologies support personalized learning, timely feedback, and data-driven instructional decision-making. These studies collectively show that AI-enabled instructional tools can strengthen teaching effectiveness and student performance. However, some studies have argued that the impact of AI tools may be limited in institutions with low digital readiness, insufficient training, or poor integration into pedagogy. A notable aspect of the present finding is that AI-enabled instructional tools made one of the strongest contributions to student learning outcomes among the predictors examined, highlighting the growing importance of intelligent learning technologies in higher education.

The findings indicated that digital infrastructure quality significantly predicted student learning outcomes in higher education institutions. This means that reliable internet connectivity, stable electricity supply, access to digital devices, and institutional technical support play a crucial role in enabling effective technology-supported learning. This result agrees with Czerniewicz et al. (2020), Dhawan (2020), Adarkwah (2021), UNESCO (2021), and Bates (2024), who emphasized that digital infrastructure is fundamental to successful online and blended learning environments. These studies showed that inadequate infrastructure limits access to digital learning tools and reduces academic participation and performance. On the other hand, some earlier research suggested that student motivation and instructional quality could compensate for infrastructure limitations in certain contexts. What is significant about this finding is that digital infrastructure quality emerged as a strong predictor of student learning outcomes, confirming that technology-based education cannot be effective without adequate institutional and technological support systems.

The study further showed that Learning Management System usage, artificial intelligence enabled instructional tools, and digital infrastructure quality jointly and significantly predicted student learning outcomes in higher education institutions. The combined model explained a substantial proportion of the variance in student learning outcomes, indicating that technology integration in higher education is most effective when digital platforms, intelligent instructional tools, and infrastructure function together. This finding aligns with Bond et al. (2021), Bates (2024), Holmes et al. (2019), and Turnbull et al. (2021), who emphasized that the effectiveness of educational technology depends on the interaction between infrastructure readiness, instructional design, and digital tools. However, some studies have examined these variables independently and reported weaker predictive effects when they are not integrated within a coordinated institutional strategy. A particularly important aspect of this finding is that the joint model produced stronger predictive power than any single variable alone, demonstrating that student learning outcomes in technology-mediated environments depend on a holistic digital learning ecosystem rather than isolated technological interventions.

Conclusion

This study investigated how Learning Management System usage, artificial intelligence-enabled instructional tools, and digital infrastructure quality predict student learning outcomes in higher education institutions. The findings demonstrated that each of these variables independently contributes significantly to student learning outcomes. This implies that students learn more effectively when they actively engage with LMS platforms, when AI-enabled instructional tools are integrated into teaching, and when institutions provide reliable digital infrastructure. The study also revealed that the combined influence of LMS usage, AI-enabled instructional tools, and digital infrastructure quality provides a stronger prediction of student learning outcomes than any single factor alone. This indicates that technology-supported learning in higher education is most effective when digital tools, instructional innovation, and infrastructure development are implemented together as part of a coordinated institutional strategy. Furthermore, the findings highlight the growing importance of AI-enabled instructional tools as a major contributor to student learning outcomes, followed closely by digital infrastructure quality and LMS usage. This suggests that higher education institutions must move beyond basic technology adoption toward meaningful integration of intelligent learning systems supported by reliable infrastructure.

Notwithstanding, the study concludes that improving student learning outcomes in higher education requires a holistic digital learning ecosystem that combines functional LMS platforms, AI-supported instructional practices, and strong digital infrastructure. Without this integrated approach, the full potential of educational technology in higher education may not be realized.

Recommendation

1. Universities should strengthen Learning Management System integration by encouraging lecturers to use LMS platforms for instructional delivery, assessment, feedback, and student interaction rather than limiting them to administrative functions.
2. Higher education institutions should promote the adoption of AI-enabled instructional tools through staff training, institutional support, and curriculum integration to enhance personalized learning and student engagement.
3. Government and university management should invest in digital infrastructure, including stable internet connectivity, reliable electricity supply, digital devices, and technical support services to ensure effective technology-mediated learning.
4. Lecturers should receive continuous professional development training on digital pedagogy, LMS utilization, and AI-supported teaching strategies to improve instructional effectiveness.
5. Institutional policies should support coordinated technology integration, ensuring that LMS platforms, AI instructional tools, and digital infrastructure function together to improve student learning outcomes

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