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Evaluating Student Readiness for Computer-Based and Adaptive Assessment in Engineering Education in Nigeria

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Abstract

The rapid integration of digital technologies in higher education has transformed assessment practices, with computer-based and adaptive assessment systems gaining increasing attention as viable alternatives to traditional methods. However, concerns remain about whether students in resource-constrained environments possess the readiness required to engage effectively with these systems. This study therefore investigates the readiness of engineering undergraduate students for computer-based and adaptive assessment systems in higher education. A cross-sectional survey research design was adopted, targeting undergraduate engineering students, with 190 participants selected as the study sample. A structured questionnaire employing a five-point Likert scale was used to collect data on digital tool usage, perceived effectiveness, engagement, confidence, and infrastructural challenges. Data were analysed using descriptive statistics, correlation analysis, regression modelling, and reliability testing, all conducted with Python-based analytical tools. The findings reveal a moderate level of digital readiness among students, with relatively higher scores in collaboration and confidence. Critical barriers were identified, including poor internet connectivity, unstable power supply, and insufficient training. Regression analysis indicated that digital learning variables contribute to variations in student confidence, though multicollinearity among predictors was observed, while reliability testing yielded a Cronbach's alpha of 0.55, reflecting moderate internal consistency. The study concludes that although students demonstrate a positive disposition toward digital and adaptive assessment systems, effective implementation demands substantial institutional investment in infrastructure and capacity development. It is therefore recommended that higher education institutions in resource-constrained contexts prioritise digital infrastructure upgrades and structured training programmes to support the scalable and equitable adoption of adaptive assessment in engineering education.

Keywords: Blended Student Readiness, Engineering Education, Digital Learning Infrastructure, Students

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INTRODUCTION

Technology continues to drive significant transformation in educational assessment across multiple dimensions. It enhances the accuracy and efficiency of measuring student performance, facilitates data collection and analysis, and supports timely feedback for both learners and educators (Lampodu et al,2026) . In addition, digital assessment systems enable the evaluation of cognitive, affective, and psychomotor domains while also capturing the broader context of teaching and learning processes (Mullers et al., 2026).

In recent years, higher education institutions have increasingly adopted computer-based assessment systems as part of broader digital learning initiatives. These systems provide opportunities for improved flexibility, faster grading, and enhanced student engagement. More importantly, the emergence of adaptive assessment technologies has introduced a more personalized approach to evaluation, where test items are dynamically adjusted to match individual student ability levels. This approach not only improves measurement precision but also reduces testing time and enhances the . assessment experience (Song & Wang, 2026). Despite these advantages, the successful implementation of computer-based and adaptive assessment systems depends largely on student readiness and the availability of supporting infrastructure. While students may demonstrate positive attitudes toward digital learning, challenges such as limited access to reliable internet connectivity, inconsistent power supply, and insufficient training continue to pose significant barriers, particularly in developing educational contexts (Sigalla & Sanga, 2026). In engineering education, where practical skills, simulations, and problem-solving are integral components of learning, the integration of digital and adaptive assessment systems presents both opportunities and challenges. However, despite existing studies on computer-based assessment, limited research has specifically examined student readiness for adaptive testing in engineering education within developing contexts. Although studies on digital and adaptive assessment systems have grown considerably, most have been conducted in well-resourced settings, with little attention given to engineering students in African and developing country contexts where infrastructural constraints significantly shape technology engagement. This gap makes it difficult to draw transferable conclusions for such environments. This study therefore aims to evaluate the readiness of engineering students for computer-based and adaptive assessment systems, specifically examining digital tool usage, perceived effectiveness, engagement, confidence, and adoption challenges. The findings are expected to inform the design and implementation of scalable, context-appropriate adaptive assessment systems in resource-constrained higher education institutions

LITERATURE REVIEW

The integration of technology into educational assessment has led to significant advancements in how student learning is measured and evaluated. Computer-based assessment systems have become increasingly prevalent in higher education due to their ability to enhance efficiency, accuracy, and accessibility (Zakariya et al., 2026). These systems support automated scoring, immediate feedback, and flexible test administration, making them particularly suitable for large and diverse student populations. However, while such benefits are widely acknowledged, scholars have cautioned that the effectiveness of these systems is not uniform across all contexts. Chen (2026) notes that the capacity to leverage learner data for instructional improvement depends heavily on institutional readiness and data management capabilities, conditions that are often absent in developing educational environments. A major development within this domain is the emergence of computerised adaptive testing (CAT), which shifts assessment from fixed formats to dynamic, individualised approaches (El Msaver et al., 2026). Adaptive systems adjust item difficulty in real time based on student responses, yielding more precise ability estimates and shorter test lengths (Huang et al., 2009). Weiss and Şahin (2024) further demonstrate that adaptive assessment enhances the overall student experience. Nevertheless, these findings largely originate from technologically advanced settings, and their applicability to resource-constrained environments remains insufficiently examined. The assumption that adaptive systems can be readily deployed without addressing underlying infrastructural deficits represents a critical gap in the literature. Student readiness is consistently identified as central to the successful adoption of digital assessment systems, encompassing digital literacy, prior technology experience, confidence, and attitudes toward computer-mediated learning (Cramarenco et al., 2023; Ozden, 2004; Dunn et al., 2003; Llamas et al., 2013). While these studies broadly report positive student perceptions toward digital assessment, particularly regarding convenience and immediate feedback, their conclusions are not without contradiction. Several studies indicate that positive perceptions do not reliably translate into functional readiness, as disparities in digital competence and device access introduce significant variation in student engagement. This distinction between attitude and actual readiness is underexplored in the literature, particularly within engineering education.

Infrastructural and institutional factors further complicate the adoption of digital assessment in developing contexts. Poor internet connectivity, unreliable power supply, limited device access, and inadequate technical support remain persistent barriers that undermine both the reliability and fairness of computer-based assessments. While this challenge is acknowledged in the broader literature (Adeoye et al., 2025), few studies have empirically quantified how these barriers specifically affect engineering students' readiness and confidence. Most existing research treats infrastructure as a background condition rather than a variable worthy of systematic investigation, thereby limiting the practical utility of their findings for institutions operating under such constraints. The Technology Acceptance Model (TAM), proposed by Davis (1989), offers a useful theoretical lens for understanding technology adoption in educational contexts. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of users' acceptance of technology. Within computer-based assessment, students are more likely to engage with digital systems they perceive as beneficial and accessible. However, critics of TAM argue that the model oversimplifies adoption behaviour by underemphasising contextual and structural factors such as infrastructure quality and institutional support, which are particularly salient in developing-country settings. This study therefore applies TAM while acknowledging these limitations, using it as a guiding but not exclusive framework.

Within engineering education specifically, digital assessment tools offer considerable potential for supporting simulation-based learning, visualising complex concepts, and enabling continuous evaluation of problem-solving skills (Shute et al., 2017; Csapo, 2011). Yet the realisation of these benefits depends on both student preparedness and enabling institutional conditions. Existing studies in this area tend to focus on pedagogical outcomes rather than student readiness, and rarely situate their findings within African or comparable developing-country contexts where structural constraints are more pronounced. This study therefore addresses these gaps by providing empirical evidence on the readiness of engineering undergraduate students for computer-based and adaptive assessment systems in a resource-constrained African higher education context. Unlike prior studies that treat readiness as a peripheral concern or assume adequate infrastructure, this study foregrounds both dimensions simultaneously, contributing context-specific insights that can inform more equitable and scalable implementation strategies for adaptive assessment in engineering education.

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Theoretical Framework

This study is grounded in the Technology Acceptance Model (TAM), originally proposed by Davis (1989), which posits that users' adoption of technology is primarily determined by two constructs: perceived usefulness and perceived ease of use. In the context of this study, TAM informs the key variables examined, including students' confidence, engagement, and attitudes toward computer-based and adaptive assessment systems. Students who perceive digital assessment tools as useful and easy to navigate are more likely to demonstrate higher readiness and willingness to adopt them. TAM therefore provides the conceptual lens through which the relationships between digital learning variables and student readiness are interpreted.

MATERIAL AND METHODS

This study adopted a mixed-methods research approach using a convergent design to examine students' readiness for computer-based and adaptive assessment systems, as illustrated in Figure 1 (Smith & Hasan, 2020). Quantitative and qualitative data were collected simultaneously through a structured questionnaire to provide a broader understanding of students' experiences and perceptions. The questionnaire responses were exported from Google Forms into Microsoft Excel and analyzed using Python programming language. Data processing was carried out with the aid of libraries such as pandas, numpy, and statsmodels. Prior to analysis, the dataset was screened to remove incomplete entries, handle missing values, and convert categorical responses into numerical form where necessary.

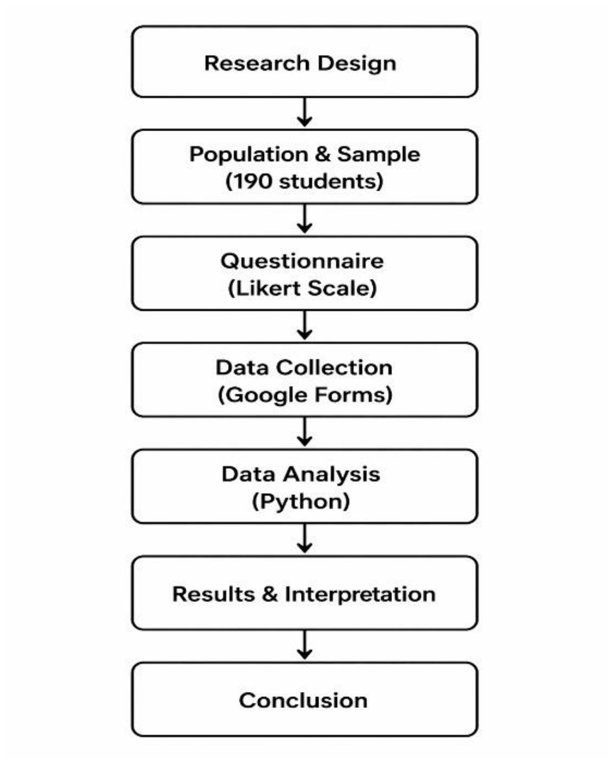

Figure 1: Research flow chat.

Population and Sample

The study involved 190 undergraduate engineering students selected using a convenience sampling approach, wherein participants were drawn from accessible cohorts within the researchers' institution. While convenience sampling offers practical advantages including ease of access, reduced recruitment time, and cost-effectiveness it carries inherent limitations for external validity and generalisability. Specifically, findings derived from a single institutional context may not be fully transferable to undergraduate engineering populations across different universities, cultural settings, or educational systems. This sampling method may also introduce selection bias, as students who are more accessible or willing to participate may differ systematically from those who are not. Nevertheless, convenience sampling remains widely adopted in educational research at the exploratory and preliminary stages, where the primary aim is to examine relationships among variables rather than to make population-level inferences (Cohen et al., 2018; Etikan et al., 2016). The voluntary nature of participation and anonymous data collection were employed to minimise response bias and uphold ethical standards. Future studies are encouraged to employ probability-

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based sampling strategies such as stratified or random sampling across multiple institutions to enhance the representativeness and broader applicability of the findings.

Data Collection Instrument

Data were collected using a structured questionnaire administered via Google Forms. The instrument was developed based on a review of existing validated scales in digital readiness and computer-based assessment research, with items adapted from Cramarenco et al. (2023), Llamas-Nistal et al. (2013), and Özden (2004), and contextualised to reflect the engineering education environment in Nigeria. The instrument was organised around five construct domains: (1) digital tool usage, measuring the frequency and variety of digital tools used in academic learning; (2) perceived effectiveness, capturing students' judgements of the usefulness of digital platforms for learning; (3) engagement, reflecting the degree of active participation in digital learning activities; (4) confidence, assessing students' self-efficacy in using computer-based systems; and (5) infrastructural challenges, identifying barriers related to connectivity, power supply, and device access.To establish content validity, the draft instrument was reviewed by two experts in educational technology and engineering education, who evaluated each item for clarity, relevance, and construct alignment. Their feedback informed minor revisions to item wording before finalisation. A pilot test was subsequently administered to 20 undergraduate students from a comparable cohort not included in the main study, to assess item comprehensibility and estimate preliminary reliability. Based on pilot feedback, three items were slightly reworded for improved clarity. The finalised instrument employed a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with open-ended items included to capture qualitative insights and provide contextual depth to the quantitative responses.

Data Analysis

Quantitative data were analyzed using descriptive statistics, specifically mean scores and standard deviations. The interpretation of Likert scale responses was categorized as follows: 1.0–2.4 (low), 2.5–3.4 (moderate), and 3.5–5.0 (high). Qualitative responses were examined using thematic analysis to identify recurring patterns and key themes. The internal consistency of the instrument was assessed using Cronbach’s alpha coefficient.

RESULTS

Correlation Analysis

A correlation analysis was conducted to examine the relationships between the study variables (see appendix). The results indicate varying degrees of association among the variables. Positive correlations suggest that increased use of digital tools is associated with higher levels of understanding, engagement, and confidence. These findings support the assumption that digital learning tools play a role in enhancing student learning experiences.

Regression Analysis Section

A multiple linear regression analysis was conducted to examine the factors influencing students' perceptions that digital learning tools improve their understanding of engineering concepts. The overall model was statistically significant, $F(9, 179) = 46.50$, $p < .001$, explaining 70.0% of the variance in students' perceived understanding ($R^2 = 0.700$, Adjusted $R^2 = 0.685$). The results indicate that several digital learning factors significantly predict students' understanding. Frequency of digital tool usage was a significant positive predictor ($\beta = 0.242$, $p < .001$, 95% CI [0.120, 0.365]). Similarly, simulation software that helps visualize engineering processes had a strong positive effect ($\beta = 0.308$, $p < .001$, 95% CI [0.180, 0.435]). Online collaboration tools also significantly contributed to improved understanding ($\beta = 0.135$, $p = .049$, 95% CI [0.001, 0.268]). In addition, students' confidence in using digital technologies was a significant positive predictor ($\beta = 0.154$, $p = .014$, 95% CI [0.032, 0.277]).

Other variables, including digital assessments and feedback ($\beta = -0.047$, $p = .478$), engagement during lectures ($\beta = 0.128$, $p = .103$), poor internet connectivity ($\beta = 0.080$, $p = .161$), inconsistent power supply ($\beta = -0.031$, $p = .608$), and training received on digital tools ($\beta = 0.040$, $p = .497$), were not statistically significant predictors. Diagnostic tests indicated no serious autocorrelation in the residuals (Durbin–Watson = 1.95). Although the Jarque–Bera test suggested a deviation from normality ($p < 0.05$), regression estimates are generally robust for large samples. Multicollinearity diagnostics showed acceptable levels (VIF values ranged from 1.70 to 3.88), indicating no severe multicollinearity concerns among predictors. While the condition number suggested potential numerical sensitivity, VIF values provide a more reliable indication, confirming that multicollinearity is not severe enough to invalidate the model.

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Quantitative Findings

Descriptive statistics were computed to evaluate students' digital readiness across key learning dimensions. The mean scores indicate an overall moderate level of readiness, with slight variation across variables.

Table 1 presents the descriptive statistics of the measured variables. Digital tool usage recorded the lowest mean score (M = 2.55), indicating relatively limited engagement with digital tools. In contrast, collaboration (M = 2.95) and confidence (M = 2.95) recorded the highest mean values, suggesting that students are relatively comfortable interacting and participating in digital learning environments. Other variables, including understanding (M = 2.80), simulation (M = 2.80), assessment (M = 2.90), and engagement (M = 2.85), fall within the moderate range.

Table 1: Descriptive Statistics of Digital Learning Variables (n = 190)

Variable	**Mean**	**Interpretation**
Usage	2.55	Low
Understanding	2.80	Moderate
Simulation	2.80	Moderate
Collaboration	2.95	Moderate-High
Assessment	2.90	Moderate
Engagement	2.85	Moderate
Confidence	2.95	Moderate-High

To provide a visual representation of these findings, Figure 2 illustrates the distribution of mean scores across the digital readiness variables. The figure highlights the relatively higher performance in collaboration and confidence compared to other dimensions.

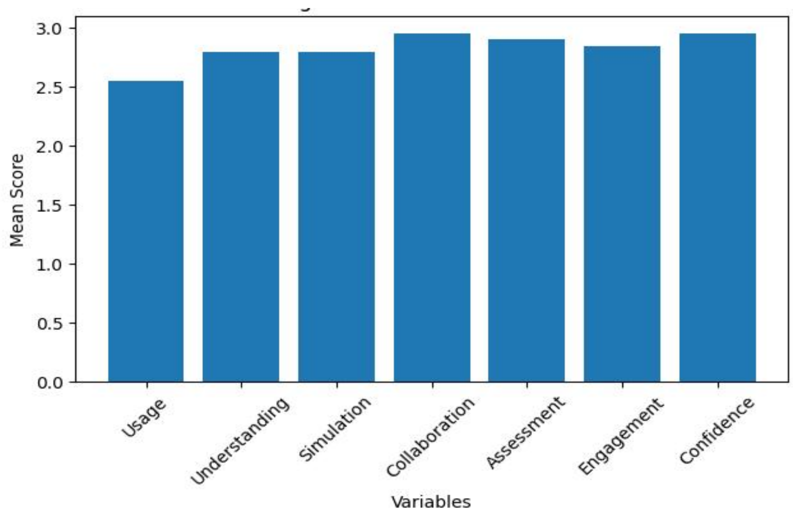

Figure 2: Digital Readiness of Students here

Further comparison of the digital learning factors is presented in Figure 3, which shows the variation in mean scores across all variables. The figure confirms that while no variable reached a high readiness level, most fall within the moderate category, indicating a consistent but not advanced level of digital competence among students.

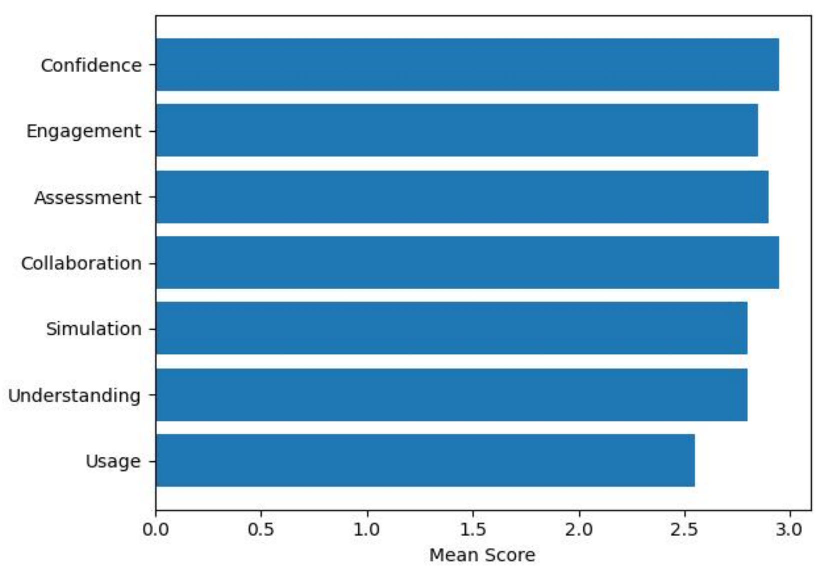

Figure 3: Comparison of Digital Learning Factors

The ranking of digital readiness variables is summarized in Table 2. Collaboration and confidence are jointly ranked highest (M = 2.95), followed by assessment (M = 2.90) and engagement (M =

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2.85). Usage ranks lowest (M = 2.55), reinforcing the observation that practical interaction with digital tools remains limited.

Table 2: Ranking of Digital Readiness Variables

Rank	Variable	Mean
1	Collaboration	2.95
1	Confidence	2.95
3	Assessment	2.90
4	Engagement	2.85
5	Understanding	2.80
5	Simulation	2.80
7	Usage	2.55

This ranking is further illustrated in Figure 4, which provides a comparative visualization of the relative positions of each variable.

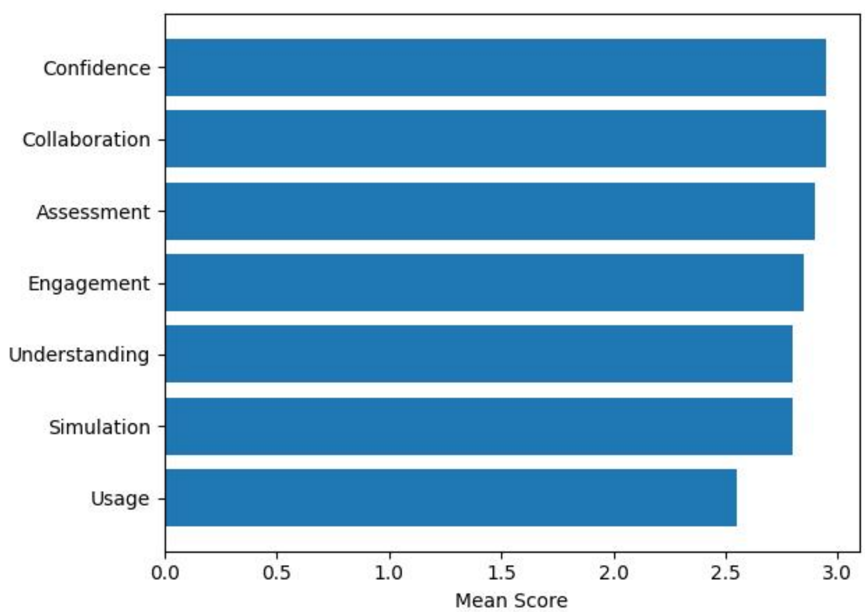

Figure 4: Ranking of Digital Readiness Variables

The quantitative findings indicate that students demonstrate moderate readiness, with stronger tendencies toward collaborative engagement and confidence, but weaker levels of active digital tool usag

Challenges Affecting Digital Learning

The analysis of challenges reveals that infrastructural and capacity-related issues significantly affect digital readiness. As shown in Table 3, poor internet connectivity was identified as the most critical barrier (38.9%), followed by power supply issues (29.5%) and lack of training (28.9%). Software and device limitations were also noted as moderate constraints.

Table 3: Key Challenges Affecting Digital Learning

Challenge	Percentage (%)	Interpretation
Poor Internet Connectivity	38.9%	Major Barrier
Power Supply Issues	29.5%	Significant Barrier
Lack of Training	28.9%	Moderate Barrier
Software/Device Limitations	~25%	Moderate Barrier

These findings indicate that infrastructural deficiencies and limited technical preparedness remain central obstacles to effective digital learning implementation.

Qualitative Findings

Thematic analysis of open-ended responses revealed several perceived benefits and challenges associated with digital learning.Students reported that digital tools contribute to improved understanding, faster learning, and enhanced visualization of complex engineering concepts. Practical skill development and collaboration were also frequently highlighted as key advantages. However, the most recurrent challenges identified include poor internet connectivity, unstable power supply, high costs associated with software and devices, and insufficient training. These findings reinforce the quantitative results, particularly regarding infrastructural limitations. Participants further suggested improvements such as enhanced internet infrastructure, provision of

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training programs, increased access to licensed software, and better integration of digital tools into teaching and learning processes.

Reliability Analysis (Cronbach's Alpha)

The internal consistency of the questionnaire was assessed using Cronbach's alpha coefficient. The analysis yielded a Cronbach's alpha value of 0.55, indicating relatively weak internal consistency among the questionnaire items. Although values above 0.70 are generally recommended for established measurement instruments, lower values may occur in exploratory studies involving multiple constructs or newly adapted instruments. The obtained reliability coefficient suggests that the items may not consistently measure a single underlying construct and that the results should therefore be interpreted with caution. This finding may reflect the multidimensional nature of the questionnaire, which was designed to assess several aspects of digital readiness, including digital tool usage, perceived effectiveness, engagement, confidence, and infrastructural challenges. Future studies should consider revising or refining questionnaire items and conducting subscale-specific reliability analyses to improve measurement consistency and strengthen the psychometric properties of the instrument.

Key Insight

The results collectively indicate that while students exhibit a positive orientation toward digital learning, their readiness is constrained by infrastructural and capacity-related challenges. This suggests that improvements in technological support and training are necessary to enable effective adoption of computer-based and adaptive assessment systems.

DISCUSSION

The findings indicate that engineering students possess a moderate level of digital readiness for computer-based and adaptive assessment. This suggests that students have acquired basic familiarity with digital learning technologies but may not yet possess the advanced competencies required for the effective implementation of sophisticated adaptive assessment systems. Similar findings have been reported in studies on digital learning adoption in higher education, where students generally demonstrate positive attitudes toward technology but often lack the comprehensive skills needed to maximize its educational benefits. The moderate readiness observed in this study may therefore reflect the ongoing transition of Nigerian universities toward more technology-enhanced learning environments.

The relatively high mean scores recorded for collaboration and confidence indicate that students are generally receptive to digital technologies and perceive them as useful for learning. This finding supports the Technology Acceptance Model (Davis et al., 1989), which argues that perceived usefulness and ease of use influence technology adoption. It also aligns with previous studies that have found positive student attitudes toward online learning platforms, digital collaboration tools, and computer-based assessments. The willingness of students to engage with digital systems suggests that resistance to technology may not be a major barrier to the adoption of adaptive assessment within engineering education. However, the study also identified significant infrastructural challenges, particularly poor internet connectivity, inconsistent power supply, and inadequate training opportunities. These findings are consistent with previous research conducted in developing countries, where technological infrastructure remains one of the most significant obstacles to the successful implementation of digital learning initiatives. While students may be willing to adopt computer-based assessments, the effectiveness of such systems depends heavily on the availability of reliable technological resources. Inadequate infrastructure may compromise assessment reliability, increase student anxiety, and create inequalities among learners who experience varying levels of access to digital resources. An important finding of this study is the relatively low Cronbach's alpha coefficient ($\alpha = 0.55$), which indicates weak internal consistency among the questionnaire items. This result may be explained by the multidimensional nature of the instrument, which measured several distinct constructs, including digital tool usage, understanding, simulation, collaboration, engagement, confidence, and infrastructural challenges. Because these constructs represent different aspects of digital readiness, a lower overall reliability coefficient is not entirely unexpected. Nevertheless, the result suggests that caution should be exercised when interpreting the findings, as some items may not measure the same underlying concept consistently. Future studies should consider refining questionnaire items, conducting pilot testing, and performing subscale-specific reliability analyses to improve measurement accuracy and strengthen the instrument's psychometric properties. The findings further suggest that readiness for adaptive assessment extends beyond student attitudes and competencies. Successful implementation requires a supportive institutional environment that includes adequate infrastructure, technical support, and continuous digital literacy

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training. Therefore, universities seeking to adopt adaptive assessment systems should prioritize investments in internet connectivity, stable power supply, staff development, and student training programs. Such measures will help bridge the gap between students' positive attitudes toward digital technologies and their actual preparedness for fully digital assessment environments, the study demonstrates that engineering students are generally willing to engage with computer-based and adaptive assessments, but their readiness remains constrained by infrastructural limitations and gaps in digital competence. Addressing these challenges is essential for ensuring that adaptive assessment systems achieve their intended benefits of fairness, efficiency, personalization, and improved learning outcomes.

CONCLUSION

This study has demonstrated that engineering students exhibit a moderate level of readiness for computer-based and adaptive assessment systems, with generally positive perceptions toward the use of digital tools in learning. While students show willingness and confidence in engaging with digital environments, their level of preparedness is not yet sufficient to support the full-scale implementation of adaptive testing systems. The findings highlight that infrastructural limitations, particularly unreliable internet connectivity and inconsistent power supply, remain significant barriers to effective adoption. In addition, the lack of adequate training further constrains students' ability to fully utilize digital assessment platforms. These challenges underscore the need for a supportive and well-resourced technological environment to ensure the reliability and fairness of computer-based assessments. For adaptive testing systems to be successfully implemented, higher education institutions must prioritize strategic investments in critical areas. These include improving internet infrastructure, ensuring stable power supply, and providing structured training programs that enhance students' digital competencies. Equally important is the need to integrate digital assessment practices gradually into the curriculum, allowing students to build familiarity and confidence over time.

Findings highlight key policy and practice implications for African higher education institutions, especially in resource-constrained settings. Policymakers and institutional leaders should prioritize infrastructure development, digital skills training, and equitable access to technology. These measures are essential for enabling scalable, reliable, and context-appropriate adaptive assessment systems in engineering education environments.

Conflicts of Interest

No conflict of interest

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APPENDIX

Appendix A: Python Code

Python Script Used for Data Analysis

```
import pandas as pd
import numpy as np
import statsmodels.api as sm

# =========================
# 1. LOAD DATA
# =========================
file_path = r"C:\Users\Akino\Downloads\DATA.xlsx"

data = pd.read_excel(file_path)

print("\n=== First 5 Rows ===")
print(data.head())

print("\n=== Column Names ===")
print(list(data.columns))
```

```
# =========================
# 2. SELECT FIRST 7 COLUMNS
# =========================
df = data.iloc[:, 0:7]

# =========================
# 3. CLEAN DATA
# =========================

# Convert Yes/No to numbers
df = df.replace({
    'Yes': 1,
    'No': 0
})

# Convert everything to numeric
df = df.apply(pd.to_numeric, errors='coerce')

# Remove empty columns
df = df.dropna(axis=1, how='all')

# Replace bad values
df = df.replace([np.inf, -np.inf], np.nan)

# Fill missing values
df = df.fillna(df.mean())

print("\n=== Cleaned Data Preview ===")
print(df.head())

# =========================
# 4. CORRELATION
# =========================
print("\n=== CORRELATION MATRIX ===")
print(df.corr())

# =========================
# =========================
# =========================
# =========================
# 5. REGRESSION (FIXED SAFE)
# =========================
```


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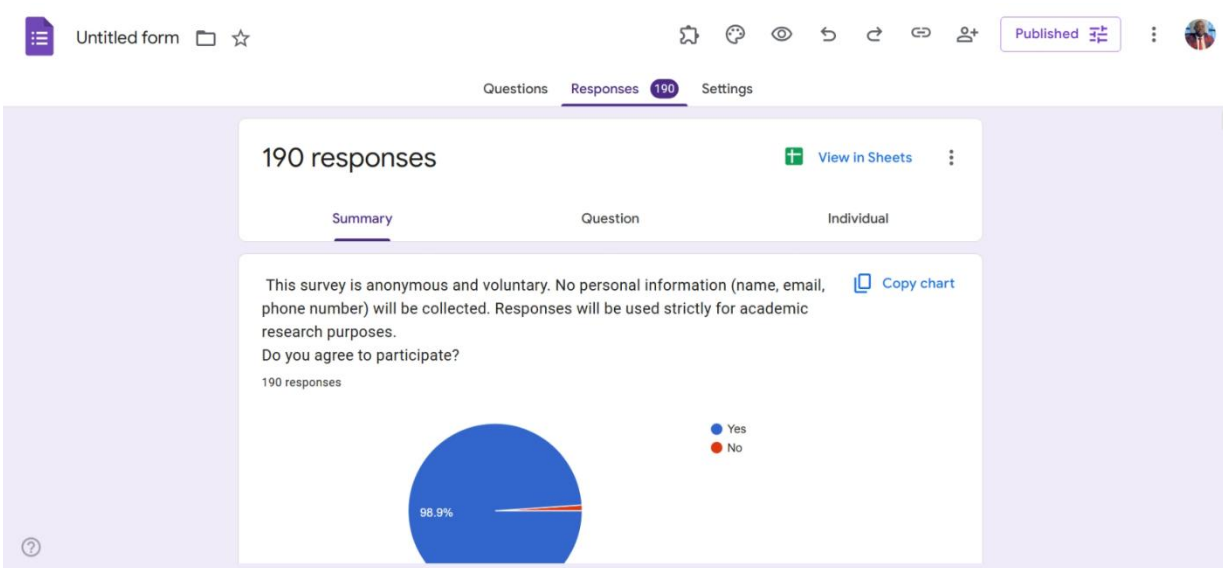
```
X = df.iloc[:, :-1]    # all except last
Y = df.iloc[:, -1]     # last column

X = sm.add_constant(X)

model = sm.OLS(Y, X).fit()

print("\n=== REGRESSION RESULT ===")
print(model.summary())
```

Appendix B: Google Form

[Untitled form - Google Forms]



Appendix C

Cronbach Alpha Result

```
[5 rows x 5 columns]

=== CRONBACH ALPHA ===
0.5466411139865548
PS C:\Users\Akino\OneDrive\Documents\PYTHON PROJECTS>
                                        Ln 80, Col 1 (1744 selected)
```

Appendix C2

Correlation Matrix Output

```
=== CORRELATION MATRIX ===
                                                  Timestamp  ...  Digital tool
s improve my understanding of engineering concepts.
Timestamp                                          1.000000  ...
                             0.002255
 This survey is anonymous and voluntary. No per...  0.188964  ...
                            -0.014358
```

Appendix C3

Regression Analysis Output and OLX

```
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix
of the errors is correctly specified.

=== MODEL FIT STATISTICS ===
R-squared: 0.7004
Adjusted R-squared: 0.6853
F-statistic: 46.4961
Prob(F-statistic): 0.000000
```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