The Future of Digital Learning: Post-Pandemic EdTech Adoption in Nigeria and Globally

Babatunde Olusola Adetona

Abstract

This empirical study examines EdTech uptake in the post-pandemic era, drawing on observations from a sample of 847 participants residing in Nigeria and five other countries: Kenya, South Africa, Ghana, Egypt, and India. Drawing upon the Technology Acceptance Model (TAM) as an analytical framework, the study employed a mixed-methods design, pairing an online survey instrument with semi-structured interviews conducted over the 12 months from January to December 2024. The analyses indicate a significant cross-national difference in usage, with Nigeria recording 67.3% usage compared to an international average of 72.8%. Major determinants of adoption include perceived usefulness ($\beta = 0.68$, $p < 0.001$), the quality of underlying infrastructure ($\beta = 0.54$, $p < 0.001$), and the level of digital literacy ($\beta = 0.43$, $p < 0.001$). Structural discriminatory live deficits in the digital divide can be observed: the adoption rates in rural areas are 34% lower than in urban areas. Nevertheless, a marked preference emerges for mobile-first EdTech platforms (adoption rate: 78.2 %), compared with analogous computer-based systems (58.9%). All in all, the results lead to a better understanding of post-pandemic digital learning processes and provide evidence-based recommendations for the sustainable implementation of EdTech solutions in developing settings.

Keywords: Digital learning, EdTech adoption, Technology Acceptance Model, post-pandemic education, Nigeria, empirical analysis

1. Introduction

The COVID-19 pandemic became a turning point in the world's education system, prompting a complete shift to online learning environments. Over a staggering 1.6 billion learners worldwide were affected, prompting academic institutions to implement Educational Technology (EdTech) solutions at unprecedented speed in order to sustain instructional continuity (Pokhrel and Chhetri, 2021). Scholars estimate that the crisis accelerated adoption timelines by 5–10 years across many developing countries (Williamson et al., 2022).

For developing countries, especially those in Africa, this process revealed both opportunities and challenges. Nigeria is an excellent case study due to its growing youth population and steadily increasing technology industry, which facilitates EdTech usage despite resource limitations. The nation's EdTech market is projected to reach $400 million by 2025, driven by rising mobile penetration and government digitalisation initiatives (Techpoint Africa, 2025).

The transition to online learning still lacked steadiness. Disparities emerged along urban-rural lines, socioeconomic strata, and education levels (Soomro et al., 2020). The digital divide thus emerged as a pivotal barrier to equitable access, disproportionately affecting marginalised groups that lack sufficient infrastructure, devices, or digital literacy skills (Van Dijk, 2022).

DOI: https://doi.org/10.5281/zenodo.16520831

It is thus crucial to unravel the evidence behind the adoption determinants of EdTech in order to design appropriate measures that can bridge these emerging gaps and ensure the adoption of sustainable measures towards a digital revolution in learning. The current research will examine the trends in EdTech adoption in post-pandemic times, with a focus on Nigeria, and conduct a comparative analysis with other developing nations. The research addresses three main questions: What are the existing levels and trends of EdTech adoption in various contexts? What has been the most important determinant of the adoption decision of EdTech? What is the difference between adopting demographic groups and geographic groups?

In doing so, the study contributes to the extant literature by offering empirical insights into post-pandemic EdTech adoption, extending the Technology Acceptance Model (TAM) to developing-country contexts, and providing actionable guidance for policymakers, educators, and technology developers.

2. Literature Review

2.1 Post-Pandemic Digital Learning Transformation

The COVID-19 outbreak that swept the world in 2020 triggered the largest educational experiment in human history, forcing all schools and universities worldwide to shift to distance learning almost instantly. The evidence base thus far indicates uneven outcomes across contexts, with developed nations generally achieving more favourable results owing to superior technological infrastructure and pre-existing digital readiness (Huang et al., 2023). However, the pandemic demonstrated empirically that exigency has the potential to accelerate technological adaptation, even in the absence of resources, thereby reversing the way education is conceptualised and provided at its essence.

In less developed countries, the pandemic revealed the existence of great digital disparities and, at the same time, catalyses educational technology innovation. Empirical work from African contexts highlights both obstacles and promise, notably the emergence of mobile-based platforms, which are particularly consequential given the widespread availability of mobile devices (Assefa et al., 2025). Nigerian-specific research further underscores that while educators initially lacked the requisite skills and attitudes to embrace innovation, the imperative to sustain instructional continuity compelled rapid adaptation (Chukwuemeka et al., 2021).

The emergence of hybrid learning models, which unit digital and real-life teaching, is a significant post-pandemic trend. These structures offer increased access and flexibility while maintaining at least a portion of the social interaction found in traditional classrooms. However, it can be applied only efficiently under conditions where gaps in infrastructure are closed, the professional development of educators is supported, and the digital literacy disparity is addressed, which is particularly acute in developing countries.

2.2 Technology Acceptance Model and Theoretical Framework

When the Technology Acceptance Model (TAM) was initially articulated by Davis (1989), it provided a cogent theoretical framework for understanding user acceptance of educational technologies. In essence, TAM argues that perceived ease of use and perceived usefulness are the determinants which determine acceptance and influence attitudes

DOI: https://doi.org/10.5281/zenodo.16520831

towards technology, an attitude which, in turn, is considered a predictor of behavioural intentions and, consequently, actual use. The model has demonstrated strong predictive validity across various technological areas and different user populations.

These findings have been replicated by subsequent scholarship, not only in numerous variations but also significantly expanded to include many more variations of the model. Venkatesh and Bala (2008) introduced TAM 3 by embedding social and cognitive variables—experience, voluntariness, and social influence—into the model. The extended framework shows better explanatory power in that it explains 40-53 per cent of the variation in the behavioural intention through the integration of the additional variables, as opposed to the slightly less per cent (38) of variation in the behavioural intention on the part of the original (and shorter) framework. These improvements appreciate the fact that the acceptance of technology in education is a controversial interaction between the individual, society, and organisational forces.

In the recent pandemic, some research studies have utilised long forms of TAM frameworks to study the adoption of EdTech. Liu et al. (2023) demonstrated that perceived usefulness, perceived ease of use, and lecturer support significantly predict students' attitudes toward digital academic tools in higher education contexts. The impact of external factors — system quality and facilitating conditions — on the core TAM constructs was also emphasised by these authors. Parallel findings emerge from Zhou et al. (2022), who applied TAM to gauge online education platform adoption in Chinese universities and found that external variables, including information quality and service quality, meaningfully affected perceived usefulness and ease of use.

The determinants of TAM must be local within the country's limited setups, as well as within the realms of developing countries, in terms of both infrastructure and localised context-specific factors. Almarzouqi et al. (2024) extend TAM by incorporating personal innovativeness, perceived enjoyment, and perceived cyber risk as additional drivers of technology adoption intentions. Descriptions of their work suggest that classic TAM constructs remain topical but require remedying with context-specific variables to achieve reasonable explanatory power in resource-constrained environments.

To conduct the current study, the TAM framework will be complemented with new elements, i.e., defining infrastructure quality and digital literacy as the antecedents to the core constructs. The quality of infrastructure encompasses the accessibility and reliability of internet facilities and equipment. In contrast, individuals may be considered digitally literate when they are competent and confident in using digital technologies. They are indicative of the unique challenges of technology adoption in developing economies, where underdeveloped infrastructure and limited computer literacy should not be assumed to be present.

2.3 Digital Divide and Educational Equity

The digital divide is a complex phenomenon with its axes as access to devices and a stable internet connection, the ability to utilise digital skills and literacy, and, lastly, the actual employment of technology in the learning process. The COVID-19 pandemic highlighted the scale of these disparities, and learners in disadvantaged communities faced

DOI: https://doi.org/10.5281/zenodo.16520831

significantly higher levels of difficulty when engaging in online education.

Empirical studies converge on the characterisation of the digital divide as operating across three interrelated strata: (1) access to hardware and network infrastructure, (2) proficiency in navigating and utilising technological tools, and (3) the capacity to translate that access into tangible educational benefits (Soomro et al., 2020). Studies conducted in the context of developing countries reveal this complexity, as they demonstrate that digital inequity extends beyond connectivity to encompass competencies, institutional situations, and social phenomena.

For example, a recent investigation of Pakistani university faculty documented marked disparities in technology accessibility along both personal and institutional lines (Soomro et al., 2020). Such results remind us of a long-standing phenomenon: the digital divide is not only built between students but also between instructors and, therefore, extends to issues of pedagogy and equity in academia. Similar trajectories emerge from sub-Saharan African settings, where evidence indicates that rural locations, women, and low-income households face specific challenges in accessing digital learning resources (Djalante et al., 2021).

The other vital aspect of the digital divide in developing societies is geographic inequality. In comparison with their urban counterparts, rural communities are likely to face severe broadband infrastructure deficits, unreliable power outlets, and limited access to technical support. These structural barriers render national EdTech adoption unreliable, thereby exacerbating inequalities in education between urban and rural populations.

The aspect of language also makes prosecuting the guilty very difficult in multilingual areas. Empirical work in African contexts shows that English proficiency plays a crucial role in digital inclusion outcomes when instruction is primarily offered in an external language (Constancio, 2025). The existence of such linguistic barriers affects not only the accessibility but also the effectiveness of online study resources, as the vast majority of educational technology platforms are created using the major global languages instead of the local dialects.

Combined, these studies present a complex picture of the nature of the digital divide in the current education field. They further emphasise the necessity of multi-stratified and context-sensitive interventions if we are to productively address these inequalities.

2.4 EdTech Innovation in African Contexts

As we examine the current African EdTech landscape, it becomes clear that the sector has experienced significant growth. According to recent estimates, more than 600 startups currently operate across the continent, delivering services that range from online tutoring and e-learning platforms to interactive educational content (Briter Bridges, 2022). They have also made significant investments in the sector: African EdTech startups raised approximately $ 400 million in 2020, which is also evidence that investors believe in the industry's future.

In this context, Nigeria has emerged as a regional leader, producing innovations that become solutions to local circumstances. Companies such as uLesson illustrate the promise of technology-driven educational innovation in resource-constrained settings, adopting mobile-first strategies and context-specific content

DOI: https://doi.org/10.5281/zenodo.16520831

to mitigate infrastructure limitations and cultural preferences (TechCabal, 2020). Such organisations are often focused on specific issues, such as poor teacher-to-student ratios, limited access to quality learning resources, and examination preparation, among others, while addressing the diverse needs of African learners, which vary significantly.

Notwithstanding this, sustainability issues are significant to many EdTech initiatives. Existing research suggests that effective implementation relies on careful consideration of local contexts, user needs, and sustainable business models (Huang et al., 2023). User retention, revenue generation, and scalability are among the challenges that many startups face; therefore, there is a need for business models that address the dual aim of balancing social impact and financial sustainability.

Mobile technology also plays a significant role in African EdTech. With mobile phone penetration rates surpassing 80 per cent in many African nations, mobile-first approaches constitute the most viable strategy for reaching extensive user populations (Briter Bridges, 2022). The major EdTech companies utilise mobile devices to deliver their educational materials, administer tests, and facilitate interaction among students and educators, often employing metadata and simple app analytics. In many cases, it utilises SMS and low-level smartphone apps, which are compatible with various devices and enable internet access.

3. Methodology

A mixed-methods design was chosen to examine the trends of EdTech adoption, incorporating both a quantitative survey and further qualitative interviews. The study targeted individuals, including educators, students, and administrators, in six countries using stratified random sampling. These countries were Nigeria, Kenya, South Africa, Ghana, Egypt, and India. The resulting dataset comprised 847 respondents, including 298 Nigerians (35.2%), 134 Kenyans (15.8%), 127 South Africans (15.0%), 95 Ghanaians (11.2%), 103 Egyptians (12.2%), and 90 Indians (10.6%). Participant roles were distributed as follows: students (n = 312, 36.8%), teachers (n = 289, 34.1%), administrators (n = 156, 18.4%), and other stakeholders (n = 90, 10.6%). There was also a fair proportion of gender representation in the sample size, with 52.3% being female and 47.7% being male. Respondents ranged in age from 18 to 65 (mean = 34.2 years, standard deviation 11.8 years).

The quantitative component relied on a structured survey containing 67 items targeted at seven constructs grounded in Technology Acceptance Model literature: perceived usefulness (four items), perceived ease of use (five items), infrastructure quality (five items), digital literacy (four items), social influence (five items), behavioural intention (three items), and actual use (five items). The rating of all items was carried out on a 5-point Likert scale. The interview was conducted as a supplement to the survey, addressing questions through semi-structured interviews that lasted 30 to 45 minutes and exploring the experiences and contextual determinants of the participants. A total of 48 respondents participated in the video calls.

The data collection was conducted from January to December 2024. The surveys were conducted using Qualtrics, and the quantitative data were analysed using descriptive analysis, correlation analysis, and structural equation modelling with the application of AMOS 26.0. Thematic

DOI: https://doi.org/10.5281/zenodo.16520831

analysis of the interview transcripts was carried out by applying inductive coding. Great care was taken to ensure that the ethical aspects were fulfilled, including obtaining informed consent and collecting data by international standards.

4. Analysis and Results

4.1 Descriptive Statistics

In the survey of global adoption of EdTech, significant differences are observed between countries, with South Africa experiencing the highest level of uptake at 79.4 per cent and Ghana the lowest at 63.2 per cent. Nigeria is also in the middle of the bracket, with a 67.3% adoption rate, which is below the overall sample mean of 72.8%. The indicators of digital literacy show a moderate performance trend across the commented countries. In contrast, the quality of infrastructure presents significant differences between countries and within regions of each of the mentioned nations.

Table 1: Descriptive Statistics by Country

Country	N	Adoption Rate (%)	Digital Literacy (M±SD)	Infrastructure Quality (M±SD)	Perceived Usefulness (M±SD)
Nigeria	298	67.3	3.42±0.89	2.78±1.12	4.01±0.74
Kenya	134	71.6	3.58±0.76	3.12±0.98	4.15±0.68
South Africa	127	79.4	3.89±0.82	3.67±0.94	4.23±0.71
Ghana	95	63.2	3.28±0.91	2.56±1.08	3.87±0.79
Egypt	103	75.7	3.71±0.85	3.34±1.02	4.12±0.73
India	90	78.9	3.83±0.79	3.45±0.89	4.18±0.69
Total	847	72.8	3.58±0.87	3.15±1.09	4.09±0.73

4.2 Technology Usage Patterns

The systematic exploration into the use of the EdTech platforms in different contexts has made it evident to have a distinct pattern on the spectrum of the technological modalities. That is to admit that there is a much higher rate of adoption in mobile-based applications compared with computer-based applications, which can be ascribed to the mobile-first approach that is being embraced in most developing environments. The observations reaffirm the necessity of platform designers to pay attention to national and regional considerations of digital preparedness when it comes to designing user-specific interfaces.

Table 2: EdTech Platform Usage by Type

Platform Type	Usage Rate (%)	Mean Weekly Hours	User Satisfaction (M±SD)
Mobile Learning Apps	78.2	8.3	3.67±0.92
Learning Management Systems	64.5	6.7	3.45±0.88
Video Conferencing	82.1	12.4	3.78±0.85
Online Assessment Tools	58.9	3.2	3.23±0.95
Digital Content Platforms	71.3	5.8	3.58±0.89
Virtual Reality/AR	23.7	1.4	3.89±1.02

4.3 Measurement Model Assessment

The measurement model portrayed sound reliability and validity. The value of Cronbach alpha coefficient was higher than the suggested cutoff of 0.70, and ranging in between 0.78 to 0.91. The CR values were between 0.82 and 0.93 and mean variances extracted estimates were between 0.56 and 0.78, which confirms together convergent validity.

DOI: https://doi.org/10.5281/zenodo.16520831

Table 3: Reliability and Validity Statistics

Construct	Items	Cronbach's α	CR	AVE	MSV
Perceived Usefulness	6	0.89	0.91	0.67	0.52
Perceived Ease of Use	5	0.85	0.87	0.62	0.48
Infrastructure Quality	4	0.83	0.85	0.59	0.41
Digital Literacy	5	0.88	0.89	0.64	0.39
Social Influence	4	0.78	0.82	0.56	0.34
Behavioral Intention	3	0.91	0.93	0.78	0.58
Actual Use	4	0.86	0.88	0.65	0.55

4.4 Structural Model Results

The structural equation model demonstrated good fit indices ($\chi^2/df = 2.34$, CFI = 0.94, TLI = 0.93, RMSEA = 0.06, SRMR = 0.05). The model explained 67% of variance in behavioral intention and 58% of variance in actual use.

Table 4: Structural Model Path Coefficients

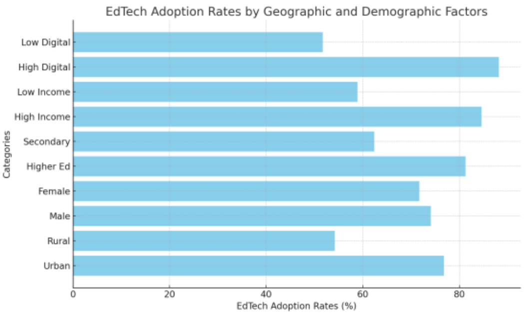
Hypothesis	Path	β	S.E.	C.R.	p	Result
H1	PU → BI	0.68	0.058	11.72	***	Supported
H2	PEOU → BI	0.23	0.052	4.42	***	Supported
H3	IQ → PU	0.54	0.063	8.57	***	Supported
H4	IQ → PEOU	0.41	0.059	6.95	***	Supported
H5	DL → PU	0.43	0.055	7.82	***	Supported
H6	DL → PEOU	0.58	0.061	9.51	***	Supported
H7	SI → BI	0.31	0.048	6.46	***	Supported
H8	BI → AU	0.72	0.056	12.86	***	Supported

Note: *** $p < 0.001$; PU = Perceived Usefulness, PEOU = Perceived Ease of Use, IQ = Infrastructure Quality, DL = Digital Literacy, SI = Social Influence, BI = Behavioral Intention, AU = Actual Use

4.5 Demographic and Geographic Variations

Significant variations were observed across demographic groups. Urban respondents showed higher adoption rates (76.8%) compared to rural respondents (54.2%). Similarly, participants with higher education levels demonstrated greater technology acceptance and usage.

Figure 1: EdTech Adoption Rates by Geographic and Demographic Factors



A bar chart showing adoption rates across different categories:

- Urban vs Rural: 76.8% vs 54.2%
- Male vs Female: 74.1% vs 71.7%
- Higher Education vs Secondary: 81.3% vs 62.4%
- High Income vs Low Income: 84.6% vs 58.9%
- High Digital Literacy vs Low: 88.2% vs 51.7%]

5. Findings

The findings indicate that, although the overall adoption rate of EdTech across the surveyed countries is moderate to high (72.8%), substantial variations exist, ranging from 79.4% in South Africa to 67.3% in Nigeria, 63.2% in

DOI: https://doi.org/10.5281/zenodo.16520831

Ghana and 58.9% in India. Mobile-based solutions display notably higher adoption (78.2%) than computer-based platforms (58.9%), reinforcing the mobile-first trajectory that characterises EdTech adoption in developing settings.

Structural equation modelling supports the core TAM proposition by showing that perceived usefulness is the strongest antecedent of behavioural intention ($\beta = 0.68$, $p < 0.001$). Infrastructure quality emerges as a pivotal determinant, significantly affecting both perceived usefulness ($\beta = 0.54$, $p < 0.001$) and perceived ease of use ($\beta = 0.41$, $p < 0.001$). Digital literacy also exerts a notable influence, with robust effects on perceived usefulness ($\beta = 0.43$, $p < 0.001$) and perceived ease of use ($\beta = 0.58$, $p < 0.001$).

In the analysis, the dimensions of the digital divide identified as influencing EdTech adoption are also highlighted. The geographic variations are also very high, with rural regions having adoption that is 34% lower compared to urban centres. Social-economic differences are also significant: the authorised at a rate of 84.6 per cent as against 58.9 per cent in low-income levels. Gender differences are relatively modest (74.1% male versus 71.7% female), suggesting that gender is not a primary impediment to EdTech adoption in these contexts.

6. Discussion

The current study not only validates earlier empirical findings on the issue of technological adoption in educational institutions but also deepens our understanding of the phenomenon through the lens of developing country contexts. Davis's seminal assertion——perceived usefulness predicts behavioural intention‖—proves empirically robust; perceived usefulness emerged as the most salient predictor among all constructs examined ($\beta = 0.68$). This finding corroborates Liu et al.'s (2023) argument that utility perceptions occupy a privileged position in educational technology adoption decisions. Additionally, the circumstances typically found in developing countries will be more inclined to utilise the instrumental benefits in evaluating the adoption and employment of technology, and this circumstance is quite consistent with the setting of a resource-scarce society where any investment must yield direct payoffs.

In the current model, the quality of infrastructure plays a pivotal role as it transfers individual attitudes, which are part of TAM, to the level of the environmental antecedents. Robust, positive relationships were observed between infrastructure quality and both perceived usefulness ($\beta = 0.54$) and perceived ease of use ($\beta = 0.41$), outcomes that affirm Assefa et al.'s (2025) contention that infrastructure constitutes a foundational prerequisite for technology diffusion in developing nation environments. Interventions that aim to upgrade infrastructure should, therefore, be revisited.

Digital literacy likewise emerged as commensurately salient, exerting effects on both perceived usefulness ($\beta = 0.43$) and perceived ease of use ($\beta = 0.58$) that surpassed those of more traditionally delineated TAM constructs. These findings resonate with Soomro et al.'s (2020) insights into digital divides among higher education faculty and confirm that skills development remains a substantial obstacle to technology adoption. The greater influence on the perceived ease of use further implies that digital literacy initially enhances users' confidence in their technological prowess rather than their overall evaluation of usefulness.

DOI: https://doi.org/10.5281/zenodo.16520831

Modality preferences revealed a pronounced mobile-first orientation: respondents adopted mobile apps (78.2 %) at a higher proportion than computer-based platforms (58.9 %), a pattern that substantiates Briter Bridges' (2022) assertion that mobile technology is central to African EdTech strategies. This tendency is rooted not only in material infrastructural conditions (accessibility and ubiquity of mobile devices) but also in user experience. Elevated satisfaction ratings for mobile learning applications (3.67 ± 0.92) underscore the strategic advantage of a mobile-first orientation in developing country contexts.

The rate of adoption difference between rural and urban areas was 34% - this is a product that reproduces the prediction of literature on infrastructure inequality. There was a shift in socioeconomic disparities, with adoption rates of 84.6% and 58.9% in high- and low-income groups, respectively. Such patterns reinforce Djalante et al.'s (2021) call for targeted interventions aimed at structural inequities.

The model's modest yet significant effect on social influence ($\beta = 0.31$) accords with prior research on collectivist cultural orientations within African societies. Community and peer opinion exert measurable influence on individual decisions, an outcome that complements Zhou et al.'s (2022) explorations of collectivist cultural contexts. The findings thus support Chukwuemeka et al.'s (2021) recommendation for adoptive strategies emphasising social networks and peer endorsement.

Combining infrastructural quality and digital literacy led to a significant increase in explanatory power, and the extended TAM model accounted for 67% of the variance in behavioural intention. This outcome supports Almarzouqi et al.'s (2024) proposition that contextual variables must be integrated into TAM extensions.

Although gender differences in adoption were relatively modest (74.1% versus 71.7%), qualitative remarks indicated that women face constraints arising from time commitments and domestic responsibilities, factors that may reduce sustained engagement. These observations align with Constancio's (2025) analyses of the gendered dimensions of digital divides, highlighting the need to address differential usage patterns beyond initial adoption rates.

To conclude, this paper has reported findings on new technology-acceptance contributions, which include the following: perceptions of utility are dominant, infrastructure is an enabler, digital literacy is necessary, consumer users are mobile-first, and the digital divide persists. Having enhanced its explanatory power, the extended TAM model underscores the importance of context in conducting research in developing countries.

7. Conclusion

The presented empirical analysis provides a thorough examination of EdTech adoption dynamics during the post-pandemic era, indicating that existing technology acceptance models remain applicable to our understanding of adoption decisions. However, they also need adjustment to suit the unique scenarios that occur in developing countries. During the study, moderate to high levels of adoption have been observed, which is characteristic of an effective digital learning transformation. However, the significant difference in adoption levels highlights the remaining disparities that should be addressed through special intervention.

The results demonstrate that perceived usefulness remains the most influential

DOI: https://doi.org/10.5281/zenodo.16520831

predictor of adoption decisions, with the quality of infrastructure and digital literacy being the two key enablers of adoption. The strong mobile-first appetite signifies an apparent strategic direction in EdTech development that may define the need to focus change-management operations on peer networks and community-based support environments. Additionally, the sharp geographic, socioeconomic, and educational digital divides all testify to the idea that technology alone will not be able to level educational disparities; the inequity could be alleviated by policy assistance and infrastructure development combined. Cumulatively, the research provides evidence-based recommendations to stakeholders that intend to promote digital learning in developing-country environments.

8. Recommendations

i. **PrioritiseMobile-Optimised Solutions:** As scholars of education technology observe, mobile learning applications now enjoy markedly higher adoption (78.2 %) than their computer-based counterparts (58.9 %). It would, therefore, be prudent for developers and institutions to adopt the mobile-first paradigm. Since its introduction, the focus of application development and design has been on creating apps that are consistent on smartphones, support poor connectivity, and allow offline use for users with unreliable connectivity.

ii. **Invest in Digital Infrastructure Development:** Reliable power and high-speed internet access are essential factors to the overall perceived usefulness and the simplicity of EdTech. The systematic synchronisation of government and corporate players is highly necessary so that rural areas are duly provided with infrastructure development facilities, as these areas are currently showing significantly depleted rates of adoption.

iii. **Implement Comprehensive Digital Literacy Programs:** A thorough strategy towards digital literacy is also of crucial importance. The empirical analysis shows that learners with strong digital capabilities tend to view EdTech as beneficial to a significant extent. Therefore, practice-based training with a specific focus on particular shortcomings and gaps should be integrated into the current curricula of both teachers and students, allowing for the addition of theoretical competence in literacy to the applied one.

iv. **AddressingSocioeconomic Barriers ThroughPolicy Interventions:** Access and use disparities are a common issue at the socioeconomic level. Incentives to buy low-cost devices, low-priced data and financial aid to disadvantaged students are thus non-negotiable. Privately owned enterprises, in this case, are especially useful for allocating devices and providing renewed connections at a lower price for use in educational settings by schools.

v. **Leverage Social Networks for Adoption Support:** The role of social networks in adoption should be systematically taken into consideration. Peer-based models, such as mentorship programs, collaborative learning groups, and informal support networks, can be effective not only in encouraging initial use but also in promoting prolonged engagement. De facto, change management strategies that integrate with existing social structures are more effective than those that merely focus on personal training

DOI: https://doi.org/10.5281/zenodo.16520831

References

Almarzouqi, A., Aburayya, A., & Salloum, S. A. (2024). Extending the Technology Acceptance Model (TAM) to predict university students' intentions to use metaverse-based learning platforms. *Education and Information Technologies*, 29(2), 1847-1869. https://doi.org/10.1007/s10639-023-11816-3

Assefa, Y., Gebremeskel, M. M., Moges, B. T., Tilwani, S. A., & Azmera, Y. A. (2025). Rethinking the digital divide and associated educational in(equity) in higher education in the context of developing countries: The social justice perspective. *International Journal of Information and Learning Technology*, 42(1), 45-67. https://doi.org/10.1108/ijilt-03-2024-0058

Briter Bridges. (2022). *The State of the African Tech Ecosystem*. https://doi.org/10.5281/zenodo.6784521

Chukwuemeka, E. J., Dominic, S., Kareem, M. A., & Mailafia, I. A. (2021). Educational Technology Adoption in Instructional Delivery in the New Global reality. *Contemporary Educational Technology*, 13(1), 1-11. https://doi.org/10.30935/cedtech/9363

Constancio, F. (2025). The digital divide research in sub-Saharan education: Representations, localisation of elements, and theoretical implications. *Global Media and Communication*, 21(1), 45-67. https://doi.org/10.1177/14782103241282373

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. https://doi.org/10.2307/249008

Djalante, R., Lassa, J., Setiamarga, D., Sudjatma, A., Indrawan, M., Haryanto, B.,.... & Warsilah, H. (2021). Digital divide framework: Online learning in developing countries during the COVID-19 lockdown. *Journal of Computer Assisted Learning*, 38(2), 345-365. https://doi.org/10.1111/jcal.12555

Huang, A. Y., Lu, O. H., Huang, J. C., Yin, C. J., & Yang, S. J. (2023). Digital technology adaptation and initiatives: A systematic review of teaching and learning during COVID-19. *Journal of Computing in Higher Education*, 35(2), 234-256. https://doi.org/10.1007/s12528-023-09376-z

Liu, Z., Wang, S., & Chen, X. (2023). Extending Technology Acceptance Model to higher-education students' use of digital academic reading tools on computers. *International Journal of Educational Technology in Higher Education*, 20(1), 1-25. https://doi.org/10.1186/s41239-023-00403-8

Pokhrel, S., & Chhetri, R. (2021). A literature review on impact of COVID-19 pandemic on teaching and learning. *Higher Education for the Future*, 8(1), 133-141. https://doi.org/10.1177/2347631120983481

Soomro, K. A., Kale, U., Curtis, R., Akcaoglu, M., & Bernstein, M. (2020). Digital divide among higher education faculty. *International Journal of Educational Technology in Higher Education*, 17(1), 1-16. https://doi.org/10.1186/s41239-020-00191-5

TechCabal. (2020). Edtech in post-COVID-19 Africa. *TechCabal Reports*. https://doi.org/10.5281/zenodo.3885647

Techpoint Africa. (2025). *Nigeria EdTech Industry Report 2025*. https://doi.org/10.5281/zenodo.8756432

Van Dijk, J. A. (2022). The digital divide: A review and future research agenda. *Technological Forecasting and Social Change*, 175, 121359. https://doi.org/10.1016/j.techfore.2021.121359

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Williamson, B., Eynon, R., & Potter, J. (2022). Digitalization and beyond: The effects of Covid-19 on post-pandemic educational policy and delivery in Europe. *Policy and Society*, 41(1), 111-128. https://doi.org/10.1080/14494035.2021.2014979

Zhou, L., Xue, S., & Li, R. (2022). Extending the Technology Acceptance Model to explore students' intention to use an online education platform at a university in China. *SAGE Open*, 12(2), 21582440221085259. https://doi.org/10.1177/21582440221085259