Determinants of Extended Reality Adoption in Universities within Kampala, Uganda: A Mixed Methods Study of Internal Factors and Institutional Support

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Abstract
The adoption of Extended Reality in higher education has been studied extensively in well-resourced settings, but far less is known about how immersive technology is taken up in universities that operate under infrastructural and financial constraints. This study examined the internal institutional factors that influence Extended Reality adoption in universities within Kampala, Uganda, and tested whether institutional support strengthens or weakens those relationships. A sequential explanatory mixed methods design was used. Quantitative data were collected from 389 respondents drawn from four Kampala universities and analyzed using IBM SPSS Statistics, and qualitative data from lecturers, students and policymakers were analyzed thematically. Multiple linear regression showed that four internal factors, namely technological readiness, human capacity, contextual adaptability and economic viability, jointly explained 49.5 percent of the variance in adoption, with technological readiness the strongest predictor. A moderated regression showed that institutional support significantly strengthened only the relationship between technological readiness and adoption, raising the explained variance to 55.2 percent. The qualitative findings explained these patterns, with device shortages, unreliable internet and power interruptions cited as the most frequent barriers. It is concluded that adoption in resource-constrained universities is best understood as a staged process in which infrastructure is the primary condition and institutional support is most valuable where infrastructure investment is concerned.

Keywords: Extended Reality, Technology Adoption, Higher Education, Institutional Support, Moderated Regression, Mixed Methods, Uganda

1. Introduction

Extended Reality, which covers augmented reality, virtual reality and mixed reality, is increasingly presented as a means of transforming teaching and learning in higher education. Most of the evidence on its adoption originates in institutions with dependable electricity, campus connectivity and dedicated laboratories, and the transferability of that evidence to resource-constrained settings cannot be assumed. Universities in Kampala, Uganda, present a setting in which enthusiasm for digital learning frequently meets infrastructural and socioeconomic limits, which makes the region a useful context in which to test what actually drives adoption.

This paper reports the methodology and empirical findings of a study whose objective was to develop a contextual understanding of Extended Reality adoption by examining four internal institutional factors, namely technological readiness, human capacity, contextual adaptability and economic viability, together with the moderating role of institutional support systems. The study was guided by the Technology-Organization-Environment framework and the Technology Acceptance Model, with the Resource-Based View providing the rationale for treating institutional support as a moderator rather than an independent predictor. Comparable recent work has similarly combined these frameworks to explain technology adoption in higher education, and has found that institutional and contextual conditions shape the strength of individual and organizational adoption effects (Jeilani and Abubakar, 2025) [1].

2. Research Methodology

2.1 Research Philosophy and Design

The study adopted a pragmatic philosophical position, which priorities the research problem and the practical question of what works over allegiance to a single ontology or epistemology (Creswell, 2017) [2]. Pragmatism justified the use of mixed methods, since it allowed the collection of both quantitative data to measure relationships and qualitative data to explain them. A sequential explanatory mixed methods design was used, in which quantitative data were collected and analyzed first and qualitative data were then used to interpret and enrich the statistical results. The study was cross-sectional, since data were collected at a single point in time, and analytical, since it tested relationships between variables rather than merely describing them.

2.2 Study Location and Population

The study was conducted in Kampala, the principal centre of higher education and internet activity in Uganda. Four universities were selected to reflect different institutional types: Makerere University, a large public research university; ISBAT University, a private technology-focused institution; Kampala International University, a large private multidisciplinary university; and Kyambogo University, a public institution with strong traditions in teacher education and technical training. The study population comprised 11,863 people, made up of 11,765 students, 80 lecturers and 18 administrators, drawn from these four institutions. These three stakeholder categories were chosen because they are directly involved in the use, implementation and governance of Extended Reality in higher education.

2.3 Sampling Procedure and Sample Size

Yamane's formula was used to determine the statistically required minimum sample size for the large student population, using a margin of error of 0.05 (MohanaSundaram, 2024) [3]. The calculation, shown in Table 1, produced a required student sample of 387. Because official, up-to-date enrolment records were not accessible at the time of data collection, the final sample was drawn through convenience sampling, with respondents selected on the basis of availability and willingness to participate (Golzar, 2022) [4]. The Yamane calculation therefore served as a benchmark for sample adequacy rather than as the basis for proportional stratified selection, and the achieved distribution across institutions is reported in the results with that limitation in mind. Follow-up reminders were sent in cases of non-response, and response rates were monitored throughout data collection.

Table 1: Yamane's Formula Applied to Derive the Student Sample Size

Formula	Calculation for the Student Population
$n = N / (1 + Ne^2)$	$n = 11{,}765 / [1 + 11{,}765 \times (0.05)^2] = 386.9 \approx 387$
n = sample size	N = 11,765 (student population)
N = population size	e = 0.05 (margin of error)
e = margin of error	Required student sample = 387

2.4 Data Collection Instruments

Three instruments were used. A structured questionnaire, built around five-point Likert items aligned to each study variable, was administered to students and lecturers. A semi-structured interview guide was used for detailed discussions with administrators and lecturers. An observation checklist was used during pilot Extended Reality sessions to record usability and engagement. Each instrument was pilot-tested with a small group of participants, comprising ten students, five lecturers and two administrators, drawn from an institution not involved in the main study, and the instruments were refined for clarity and relevance on the basis of the pilot feedback.

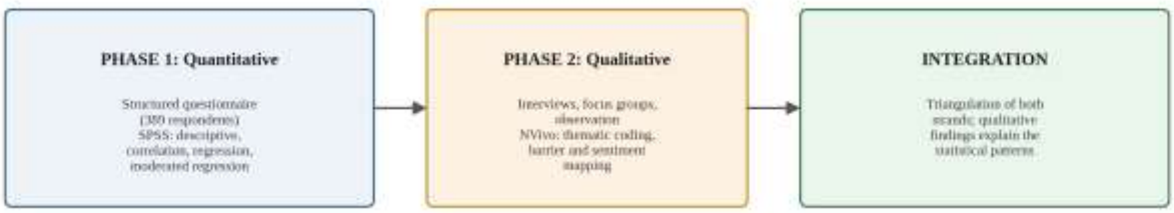
2.5 Validity, Reliability and Trustworthiness

Content validity was established by aligning questionnaire items with the theoretical constructs and having them reviewed by an expert panel. Reliability was assessed using Cronbach's alpha, with a threshold of 0.70 applied to all multi-item scales, and principal component analysis was used to examine the factor structure and identify weak items. For the qualitative strand, credibility was established through triangulation and member checking, dependability through a documented audit trail, and confirmability by ensuring conclusions were grounded in the data and by reflexively bracketing researcher assumptions.

2.6 Data Analysis

Quantitative data were analyzed in IBM SPSS Statistics using descriptive statistics, Pearson correlation, multiple linear regression and moderated multiple regression. For the moderation analysis, all predictor variables were mean-centered before computing interaction terms in order to reduce multicollinearity arising from product terms (Aiken and West, 1991) [5], and variance inflation factor diagnostics were used to confirm that multicollinearity remained within acceptable limits. Qualitative data were analyzed thematically in NVivo, with interview transcripts coded into themes and subthemes that were then used to interpret the statistical results. Figure 1 summarizes the sequential explanatory design and the analytical role of each strand.

Figure 1: Sequential Explanatory Mixed Methods Design



2.7 Ethical Considerations

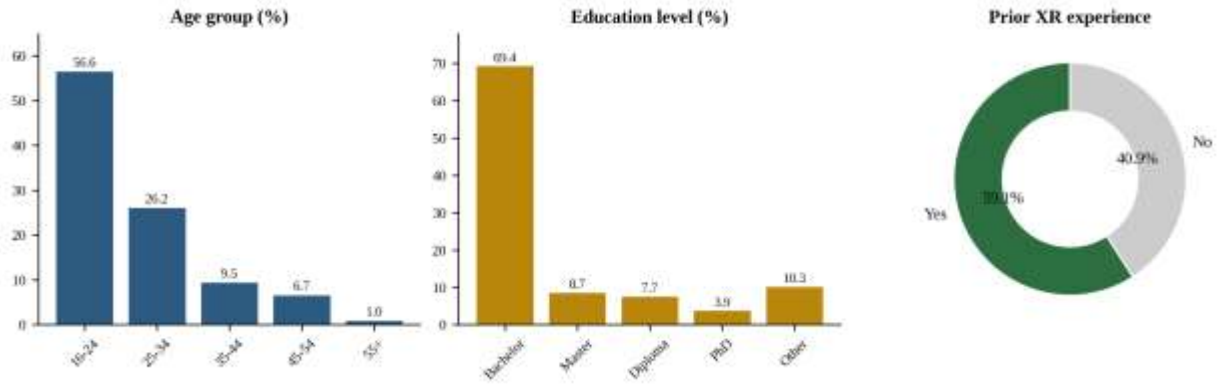
Ethical clearance was obtained from the ISBAT University Faculty of Graduate Studies and Research, and permission was sought from the administration of each participating university before data collection began. Participation was voluntary and based on informed consent, with participants free to withdraw at any point without penalty. Anonymity and confidentiality were maintained through the use of category labels and pseudonyms, and no names or registration numbers were collected in the quantitative survey. Research data were stored on password-protected and encrypted devices, with access restricted to the researcher and supervisors.

3. Results and Findings

3.1 Demographic Profile of Respondents

Of the 389 respondents, 256 (65.8 percent) were male, 131 (33.7 percent) were female and 2 (0.5 percent) identified as transgender. The sample was relatively young, with 220 respondents (56.6 percent) in the 16 to 24 age group and a further 102 (26.2 percent) aged 25 to 34. Most respondents were educated to at least undergraduate level, with 270 (69.4 percent) holding a bachelor's degree. ISBAT University contributed the largest share of respondents (184), followed by Kyambogo University (111), Makerere University (54) and Kampala International University (25). A majority of respondents, 230 (59.1 percent), reported some prior experience with Extended Reality. Figure 2 summarizes the demographic profile.

Figure 2: Demographic Profile of Respondents (n = 389)



3.2 Descriptive Findings

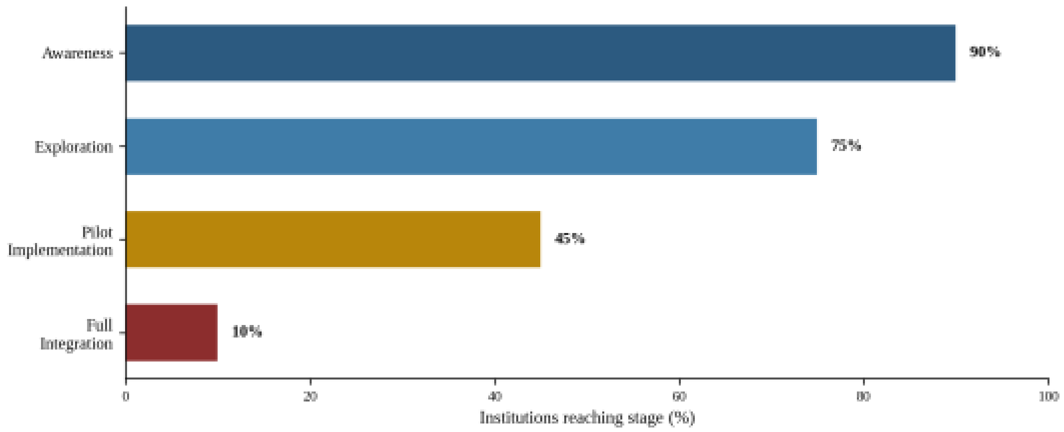
The composite means for all six constructs clustered closely around the midpoint of the five-point scale, ranging from 2.99 to 3.00, with standard deviations near 1.42 in every case, as shown in Table 2. This pattern indicates that respondents perceived technological readiness, human capacity, contextual adaptability, economic viability, institutional support and adoption itself as moderately, but not strongly, developed within their institutions. The consistency of the pattern suggests that Extended Reality provision across the sampled universities is at an emerging or transitional stage rather than an established one.

Table 2: Descriptive Statistics of the Study Constructs (n = 389)

Construct	Composite Mean	Standard Deviation
Technological Readiness (TR)	3.00	1.42
Human Capacity (HC)	2.99	1.42
Contextual Adaptability (CA)	2.99	1.42
Economic Viability (EV)	2.99	1.42
Institutional Support Systems (ISS)	3.00	1.42
XR Adoption Rate (XRA)	2.99	1.42

The qualitative data explained why perceptions clustered around neutrality. As Figure 3 shows, adoption maturity dropped sharply across stages: awareness stood at 90 percent and exploration at 75 percent, but pilot implementation fell to 45 percent and full integration to only 10 percent. A population with limited hands-on use would be expected to express moderate rather than strong views, which is consistent with the descriptive statistics.

Figure 3: Extended Reality Adoption Maturity Across Stages



3.3 Correlation Analysis

Pearson correlation showed that all four internal factors were positively and significantly correlated with adoption at the 0.01 level, as reported in Table 3. Technological readiness had the strongest association with adoption, followed by human capacity, economic viability and contextual adaptability. Correlations among the independent variables themselves were low and mostly non-significant, which indicated that the constructs were reasonably distinct and that multicollinearity was unlikely to be a serious concern.

Table 3: Correlations Between Internal Factors and Extended Reality Adoption

Internal Factor	Correlation with Adoption (r)	Significance
Technological Readiness (TR)	0.445	$p < 0.001$
Human Capacity (HC)	0.350	$p < 0.001$
Economic Viability (EV)	0.272	$p < 0.001$
Contextual Adaptability (CA)	0.267	$p < 0.001$

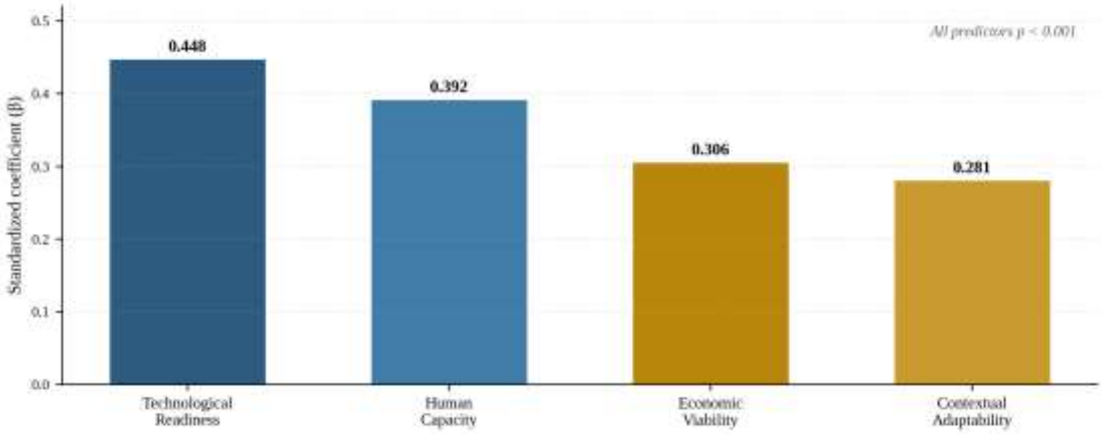
3.4 Multiple Linear Regression: Direct Effects

The multiple regression model was statistically significant ($F = 94.035$, $p < 0.001$) and explained 49.5 percent of the variance in adoption ($R^2 = 0.495$, adjusted $R^2 = 0.490$), which is a strong result for cross-sectional survey research in the social sciences. All four internal factors were significant positive predictors. Technological readiness was the strongest predictor ($\beta = 0.448$), followed by human capacity ($\beta = 0.392$), economic viability ($\beta = 0.306$) and contextual adaptability ($\beta = 0.281$), as reported in Table 4 and illustrated in Figure 4. On this basis, the null hypotheses for all four direct effects were rejected.

Table 4: Regression Coefficients for the Direct Effects on Adoption

Predictor	B	Std. Error	β	t	Sig.
(Constant)	-1.175	0.225		-5.232	0.000
Technological Readiness (TR)	0.441	0.036	0.448	12.315	0.000
Human Capacity (HC)	0.380	0.035	0.392	10.742	0.000
Contextual Adaptability (CA)	0.273	0.036	0.281	7.677	0.000
Economic Viability (EV)	0.298	0.035	0.306	8.416	0.000

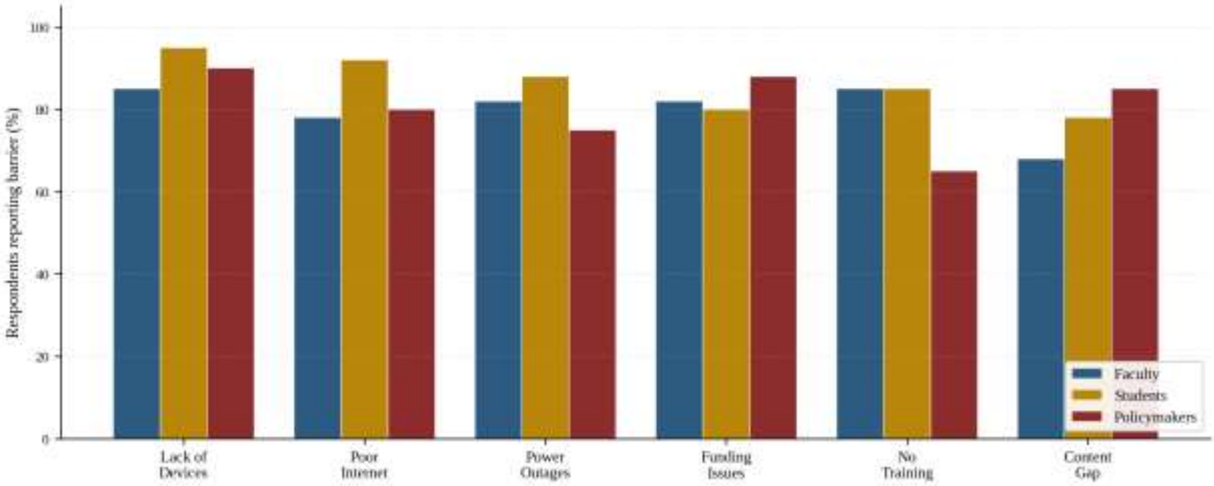
Figure 4: Standardized Regression Coefficients for the Four Internal Factors



3.5 Qualitative Triangulation of the Direct Effects

The qualitative barrier analysis, summarized in Figure 5, closely mirrored the regression ranking. The three most frequently reported barriers, namely a shortage of devices (90 percent on average), poor internet (83.3 percent) and power outages (81.7 percent), all map directly onto technological readiness, which explains why it emerged as the strongest predictor. Funding issues (83.3 percent) corresponded to economic viability, the absence of training (78.3 percent) to human capacity, and the content gap (77.0 percent) to contextual adaptability. Faculty and student perceptions of the barriers were very highly correlated (r = 0.99), while policymakers' perceptions diverged from both, pointing to a gap between policy and day-to-day practice.

Figure 5: Reported Barriers to Adoption by Stakeholder Group



3.6 Moderated Multiple Regression

A two-step hierarchical moderated regression tested whether institutional support moderated the four direct relationships. Adding institutional support and its interaction terms raised the explained variance from 49.5 percent to 55.2 percent ($R^2 = 0.552$, adjusted $R^2 = 0.542$; $\Delta R^2 = 0.058$, $p < 0.001$), as shown in Table 5. Only the interaction between technological readiness and institutional support was significant ($\beta = 0.576$, $t = 5.750$, $p < 0.001$). The interactions of institutional support with human capacity and with economic viability were not significant, and the contextual adaptability interaction was excluded because of collinearity with the economic viability interaction term. The null hypothesis of moderation was therefore only partially rejected. Figure 6 presents the resulting model.

Table 5: Regression Coefficients for the Moderated Model

Variable	B	Std. Error	β	t	Sig.
(Constant)	-1.232	0.213		-5.786	0.000
TR	0.061	0.074	0.062	0.824	0.410
HC	0.415	0.075	0.428	5.513	0.000
CA	0.385	0.072	0.396	5.365	0.000
EV	0.402	0.070	0.412	5.781	0.000
TR × ISS	0.127	0.022	0.576	5.750	0.000
HC × ISS	-0.016	0.022	-0.074	-0.720	0.472
CA × ISS	-0.032	0.022	-0.140	-1.464	0.144
EV × ISS	-0.031	0.021	-0.135	-1.450	0.148

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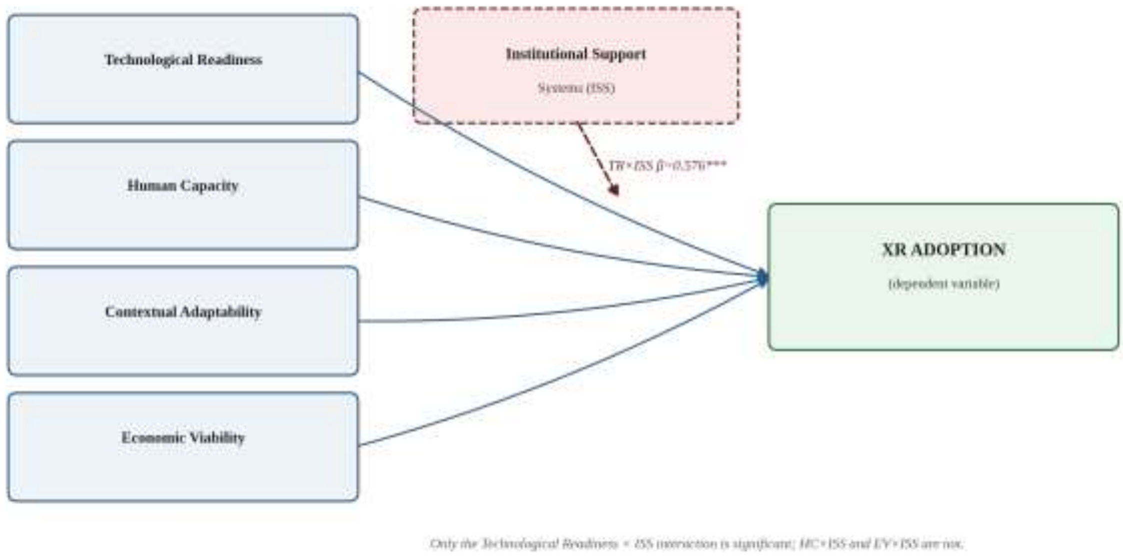
Figure 6: Moderated Model of Internal Factors, Institutional Support and Adoption



The qualitative evidence helped explain why institutional support moderated only the technological readiness path. Faculty rated institutional support as highly as they rated technical barriers (81 percent against 82 percent), whereas students rated institutional support at only 29 percent. Because infrastructure requires coordinated procurement, maintenance and policy alignment, institutional backing is most consequential where technological readiness is concerned. Training and funding, by contrast, can be advanced by committed individual lecturers or departments, or through external funders operating outside the university's internal systems, which is consistent with their non-significant interaction terms.

4. Discussion

The findings present a coherent, empirically supported account of Extended Reality adoption in a resource-constrained higher education system. Together the four internal factors and institutional support explained just over half of the variance in adoption, which is a substantial result for a cross-sectional study in an emerging economy. The prominence of technological readiness contrasts with evidence from high-income settings, where baseline infrastructure can be assumed and adoption is driven more by attitudinal factors. In Kampala, physical access to reliable electricity, functional devices and stable connectivity remains the primary obstacle, which positions technological readiness as the foundation on which any later adoption effort depends. This is consistent with comparative evidence that infrastructure and state support separate digital innovation in developed and developing higher education systems (Wang et al., 2026) [6], and with wider findings that institutional support significantly shapes technology adoption in universities (Jeilani and Abubakar, 2025) [1].
Human capacity is arguably the most actionable finding for university managers. Unlike infrastructure, which requires capital investment, educator capacity can be raised through structured, low-cost training, which suggests that training programs may yield adoption gains sooner than large infrastructure projects. This aligns with recent qualitative evidence that management support and skills development are decisive in the slow uptake of learning technologies in tertiary institutions (Murire and Gavaza, 2025) [7]. Contextual adaptability, although the weakest of the direct predictors, highlights a factor often

overlooked in adoption policy, namely that content relevance matters as much as access; this echoes findings that cultural factors significantly moderate educational technology adoption in developing countries (Al-Emran et al., 2025) [8]. Economic viability indicates that adoption is feasible even in budget-constrained institutions where cost-effective strategies, such as smartphone-based augmented reality and open-source tools, are adopted.

Finally, the moderation result carries a clear practical message. Because institutional support significantly strengthened only the technological readiness path, infrastructure investment delivers its fullest benefit when it is accompanied by leadership commitment, budget allocation and departmental coordination. Trained lecturers and external funding, by contrast, can drive adoption even where formal institutional systems are not yet fully developed. This pattern is consistent with organizational support theory, under which institutional backing converts capability into sustained use (Chatterjee et al., 2020) [9].

5. Conclusion

This study examined the internal factors and institutional support that shape Extended Reality adoption in universities within Kampala, Uganda. Technological readiness was the strongest predictor of adoption, followed by human capacity, economic viability and contextual adaptability, and institutional support significantly strengthened only the technological readiness relationship. Taken together, the findings indicate that adoption in resource-constrained universities is best understood as a staged process rather than a single decision, in which reliable infrastructure is the primary condition, human capacity is a cost-effective second priority, and content localization and sustainable financing determine whether early interest is converted into lasting use. Universities seeking to adopt Extended Reality should therefore prioritize infrastructure and pair it with institutional support, while advancing training and affordable content in parallel. Future research could extend the model longitudinally and refine the measurement of contextual adaptability and economic viability so that their interaction with institutional support can be assessed independently.

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