

INTELLIGENT SMART SYSTEMS AND AUGMENTED REALITY IN INCREASING THE EFFICIENCY OF THE EDUCATIONAL PROCESS

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ABSTRACT

This study addressed the rapid expansion of smart digital infrastructures and the need for empirically validated, data-driven learning models. The study evaluated how Intelligent Smart Systems and augmented reality affected learning efficiency, retention, engagement, cognitive load, and HCI/UX performance. A five-arm controlled quasi-experimental design was implemented over 6–8 weeks. Distributional screening of 600 students identified 200 eligible participants, followed by controlled random allocation into five groups of 40. The conditions comprised traditional instruction, an AI-enabled Smart System, visual AR, audio AR, and hybrid visual–audio AR. Baseline domain-specific performance was 72.4 ± 6.1 , with normality ($p > .12$), variance homogeneity ($p = .41$), and inter-group deviation below 3.5%. Outcomes included normalized learning gain, delayed retention, immersion, cognitive load, adaptivity, interaction error rate, usability, and interaction density. ANCOVA, repeated-measures modelling, and mediation analysis were applied. Smart/AR conditions produced normalized learning gains of 0.68–0.92. Post-test means increased from 75.4 ± 6.8 in the control group to 92.4 ± 5.1 in the hybrid group. Delayed scores ranged from 70.2 ± 7.1 to 90.1 ± 5.4 . ANCOVA confirmed a large group effect, $F(4,194) = 18.72$, $p < .001$, partial $\eta^2 = .278$. The time $\times$ condition effect was also large, $F(4,194) = 21.36$, $p < .001$, partial $\eta^2 = .306$. Mediation was significant, $ab = 0.214$, $SE = 0.052$, 95% CI [0.118, 0.324]. The resulting framework combined screening, multimodal Smart/AR intervention, cognitive–behavioural–HCI assessment, and operational deployment thresholds for evidence-based educational implementation.

Keywords: *Smart Learning, Augmented Reality (AR)-Based Education, Immersive Learning Technologies, Cognitive Efficiency, Analytical Development of the Learning Process*

1. INTRODUCTION

Relevance of the research. Digitalization has accelerated the deployment of intelligent, data-driven, and immersive learning environments. Smart/AR systems can personalize instruction, visualize complex content, and increase interaction density [1–8]. However, rapid adoption without causal validation can institutionalize costly systems that increase cognitive load or produce only short-

lived novelty effects. The central issue is therefore not technology availability, but evidence of when and under which conditions Smart/AR improves learning.

Research gap. Existing evidence remains fragmented across adaptivity, immersion, cognitive load, retention, and HCI/UX outcomes. Most studies examine these constructs separately or through short-term descriptive designs. Few controlled

studies integrate multimodal Smart/AR conditions with longitudinal retention measures and causal statistical modelling. This fragmentation limits direct comparison between traditional, Smart-only, visual-AR, audio-AR, and hybrid architectures.

Problem statement. Learning efficiency was conceptualized as a joint function of AI-driven adaptivity, multimodal immersion, cognitive-load regulation, and interface usability. These mechanisms can reinforce or counteract each other, making single-metric evaluation insufficient. A variance-stable, multi-metric design was therefore required to quantify instructional effects and identify operational deployment boundaries.

Research questions. (1) How do five instructional architectures differ in learning gain, delayed retention, cognitive load, immersion, and HCI/UX performance? (2) How stable are these differences over time? (3) To what extent do immersion and adaptation mediate the observed effects? (4) Which quantitative thresholds indicate practically viable Smart/AR deployment?

Research hypothesis. Multimodal Smart/AR architectures were expected to outperform traditional and Smart-only instruction across cognitive, behavioural, and HCI/UX outcomes. Immersion and adaptation were expected to act as partial mediators rather than peripheral interface effects. The hybrid visual-audio condition was expected to produce the strongest integrated effect.

The aim of the study. The study aimed to develop and empirically validate a multi-level framework for measuring the educational, cognitive, and interactive effects of Smart/AR technologies. It also aimed to identify deployment parameters that distinguish effective implementation from technology-driven novelty.

Scope and delimitations. The study covered five controlled instructional conditions, two higher-education institutions, and a 6–8-week intervention with delayed assessment. It evaluated learning, behavioural, cognitive, and HCI/UX outcomes. It did not estimate institutional cost-effectiveness, long-term effects beyond the delayed test, neurophysiological responses, or outcomes for students below the screening threshold.

Research objectives:

1. Build a variance-stable experimental cohort through distributional screening and threshold segmentation of the initial sample.

2. Verify baseline group equivalence using normality, homoscedasticity, and cross-group deviation diagnostics.

3. Quantify cognitive, behavioural, and HCI/UX differences across traditional, Smart-only, and Smart/AR instructional conditions using standardized metrics.

4. Estimate adjusted group effects, temporal dynamics, and mediating mechanisms using ANCOVA, repeated-measures models, and mediation analysis.

5. Translate statistically verified findings into operational recommendations and deployment thresholds for institutional Smart/AR implementation.

Research contribution. The study contributed a five-condition comparative design, a unified cognitive-behavioural-HCI metric stack, and an inferential chain combining ANCOVA, repeated measures, and mediation modelling. It further converted empirical effects into explicit performance, adaptivity, and usability thresholds for implementation decisions.

2. LITERATURE REVIEW

A literature review was required to consolidate rapidly expanding evidence on intelligent educational technologies. The synthesis focused on how adaptivity, multimodal immersion, cognitive load, interaction density, and personalization shape learning efficiency. It also identified methodological fragmentation and the limited comparability of current Smart/AR studies.

AI-AR integration followed two complementary trajectories in Lampropoulos [9] and Yao and Liang [10]. The first emphasized cognitive-perceptual optimization and ITS-level personalization, whereas the second demonstrated device-free audio-AR u-learning through multi-sensor spatialization. Their contrast showed that comparable engagement can emerge from different sensory architectures, although the underlying HCI demands differ substantially.

A related contrast emerged between the CoMoPAR architecture [11] and metaverse-scale learning environments [12]. CoMoPAR prioritized modular personalization and analytics-driven content orchestration. Metaverse systems emphasized broad socio-technical immersion, retention, engagement, and security. These approaches therefore represent architectural

precision and infrastructural expansiveness as different routes to personalized learning.

Balushi et al. [13] emphasized sensory immersion across VR/AR applications, whereas Sharma et al. [14] focused on AI/ML automation, predictive analytics, and adaptive feedback. The former pathway strengthened experiential processing; the latter optimized learning trajectories through data-driven control. Their divergence exposed a trade-off between immersion intensity and continuous algorithmic personalization.

Ateş [15] and Yadav [16] extended this contrast from discipline-specific ITS-AR to cyber-physical AR-IoT learning. Adaptive visualization improved science performance and self-efficacy, while sensor telemetry enabled context-sensitive competency development. These findings indicated that learning effects depend on architecture, instructional context, and modality rather than technological complexity alone.

Yang et al. [17] and Natarajan et al. [18] positioned these developments within broader smart-education ecosystems. The former identified stable structural pillars and multi-technology convergence, while the latter emphasized AI-supported immersive simulation and adaptive content delivery. Together, they framed systemic integration and experiential adaptivity as complementary foundations of intelligent learning.

The synthesis revealed substantial heterogeneity in immersion, adaptation algorithms, sensorimodal design, and cyber-physical integration. Positive effects on retention, engagement, and competency development were recurrent, but long-term validation and cross-context generalizability remained limited. Multimodal interoperability and HCI/UX mechanisms were also insufficiently integrated into causal designs. These gaps justified a controlled comparative study of Intelligent Smart Systems and AR using unified metrics and longitudinal inference.

3. METHODOLOGY

3.1. Research procedure

The study used a five-arm, longitudinal quasi-experimental design with controlled random assignment within the eligible cohort. The procedure comprised five sequential stages: screening and segmentation; baseline diagnostics; controlled intervention; post-test and delayed assessment; and

inferential modelling with implementation synthesis. This sequence preserved baseline equivalence while allowing direct comparison of modality-specific effects.

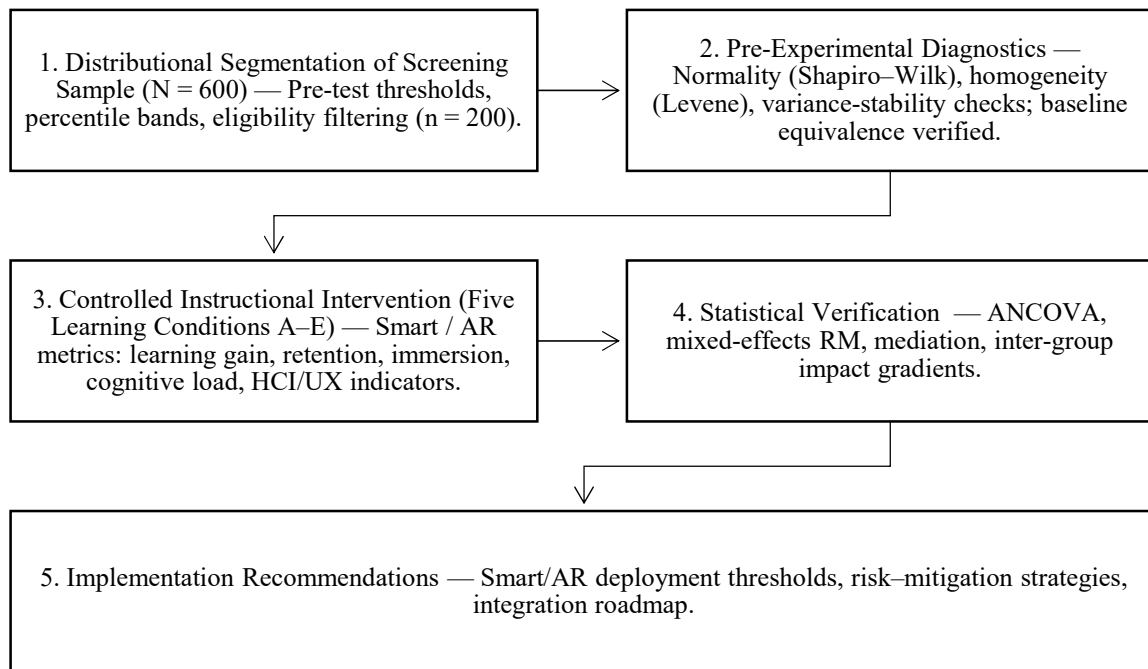


Figure 1: Structured Five-Stage Research Design for Evaluating Smart/AR-Enhanced Learning Systems (developed by the authors)

3.2 Methods

The methodology followed a staged quantitative protocol linking sample stratification, diagnostic validation, controlled intervention, multi-metric assessment, and causal statistical modelling. Each stage addressed a distinct validity requirement. Together, the stages supported high-resolution analysis of cognitive, behavioural, and HCI-mediated learning dynamics across the five instructional conditions (Table 1).

3.3 Sample

The sample was formed as an indirectly stratified cohort balanced by sex, baseline academic performance, digital literacy, and general cognitive aptitude. Cognitive screening included working-memory span and verbal-analytic reasoning indicators. The intervention lasted 6–8 weeks, which

allowed repeated exposure while limiting attrition and uncontrolled curricular drift. Outcome assessment combined a standardized achievement test, a delayed retention test, and validated measures of motivation, immersion, and cognitive load. All groups followed the same curricular sequence, instructional duration, and assessment schedule. Participants studied Computer Systems Software at Kyrgyz State Technical University or professional-language disciplines at Korolov Zhytomyr Military Institute. The shared instructional domain was Applied Technical Communication and Information Processing, including operational English, digital terminology, and subject-specific information-processing tasks.

Table 1: Methodological Design Of The Study, Developed By The Authors

Method	Purpose	Application	Outcome
Distributional Segmentation of the Initial Screening Sample (N = 600)	Derive a variance-stable, cognitively homogenous experimental cohort by filtering the initial population through knowledge-based thresholds.	Pre-test scores were subjected to distributional analysis, percentile banding, and threshold segmentation to classify learners into eligible and non-eligible strata.	A refined cohort of 200 students (33.3%) was selected from 600 candidates. The eligibility-screening score was 81.9 ± 5.8 , while subsequent domain-specific baseline testing was analyzed separately before intervention.
Pre-Experimental Diagnostics Across Screening, Distributional, and Variance-Stability Metrics	Ensure baseline equivalence and eliminate confounding variance prior to instructional intervention.	Normality (Shapiro–Wilk), homogeneity of variance (Levene), and cross-group deviation metrics were applied to pre-test, engagement, and cognitive-load indicators.	All groups demonstrated normal distributions ($p > .12$), variance homogeneity ($p = .41$), and pre-test deviations below 3.5%, confirming structural comparability and validating the experimental design.
Metric-Based Evaluation of Controlled Instructional Intervention (Five Learning and Smart/AR Conditions)	Quantify the differential cognitive, behavioural, and HCI-mediated effects of traditional, Smart, and Smart/AR instructional modalities.	Learning gain, retention index, immersion, cognitive load, adaptivity ratio, error rate, UX indices, and interaction density were computed for each group using normalized 0–1 scales.	Smart/AR modalities yielded normalized learning gains 0.68–0.92, retention-decay reduction $\approx 40\%$, immersion elevation +35–50%, and UX improvements +72–100%, demonstrating a consistent performance hierarchy favouring hybrid multimodal architectures.
Statistical Verification of Intervention Effects (ANCOVA, Repeated-Measures, Mediation, Impact Gradients)	Establish causal inference, quantify effect sizes, and validate temporal stability of instructional outcomes.	ANCOVA adjusted post-test scores for baseline differences; repeated-measures models captured temporal dynamics; mediation modelling quantified immersion-driven indirect effects; inter-group gradients assessed relative instructional impact.	ANCOVA confirmed a significant group effect, $F(4,194) = 18.72$, $p < .001$, partial $\eta^2 = .278$. The time $\times$ condition effect was $F(4,194) = 21.36$, $p < .001$, partial $\eta^2 = .306$. Mediation was significant, $ab = 0.214$, $SE = 0.052$, 95% CI [0.118, 0.324], representing 22.4% of the total effect.
Formulation of Comprehensive Implementation Recommendations	Translate validated empirical findings into actionable institutional strategies for Smart/AR adoption.	Recommendations were synthesized from metric patterns, stability thresholds, UX/HCI indicators, and identified risk factors, forming a multi-criteria deployment framework.	A structured roadmap specifying operational thresholds (performance ≥ 0.75 , adaptivity ≥ 0.40 , UX ≥ 0.80), phased deployment cycles, and risk-mitigation protocols, enabling scalable integration of intelligent immersive learning infrastructures.

Group A — Control (traditional teaching). Students received instructor-led explanations, non-interactive PowerPoint materials, printed worksheets, textbook exercises, and whiteboard demonstrations. Instruction followed a fixed teacher-regulated sequence without algorithmic adaptation or immersive content. The technological stack was limited to a standard projector and printed materials; no AI, LMS, or AR components were used.

Group B — Intelligent Smart System without AR. Students used a web-based intelligent tutoring environment with adaptive sequencing, ML-driven recommendations, automated formative feedback,

and learner-analytics dashboards. Python server-side services supported the inference layer, including gradient-boosting modules for performance-sensitive task routing. Interaction occurred through a two-dimensional desktop or tablet interface without spatial augmentation.

Group C — Smart System with visual AR. Students used marker-based and markerless AR modules integrated with the adaptive Smart System. ARCore/ARKit pipelines and Unity supported 3D models, spatial anchoring, dynamic overlays, and interactive simulations. Tablets or head-mounted displays enabled gesture-based manipulation of

instructional objects while AI-controlled sequencing adjusted task difficulty and feedback.

Group D — Smart System with audio AR (u-learning). Students completed hands-free learning tasks using spatialized audio guidance, directional sound-field synthesis, and context-sensitive narration. RGB/360° imaging, infrared occupancy sensing, and IR-assisted localization supplied positional data to the Smart System. Beamforming speaker arrays and server-side AI modules delivered adaptive audio prompts and micro-feedback according to learner location and task state.

Group E — Smart System with hybrid visual-audio AR. Students used a multimodal environment combining AI-driven adaptivity, visual AR, and spatial audio guidance. ARCore/ARKit and Unity provided anchored 3D content, while IR localization and beamforming supported context-aware audio delivery. Tablets or head-mounted displays, 360° cameras, RGB/IR sensors, and server-side inference synchronized visual simulation, narration, and adaptive feedback within one instructional workflow.

Implementation fidelity was standardized across Groups C–E through device calibration, instructor training, scripted instructional sequences, and fixed temporal blocks. AR tracking was maintained below 2.5° spatial deviation and 30 ms latency. Multi-point localization tests kept mean positional error below 5 cm. Server diagnostics recorded uptime above 98%, packet loss below 1.5%, and response latency below 120 ms. Session-level fidelity checklists verified consistent hardware, software, and content delivery.

The required sample size was determined using stringent statistical parameters: significance level $\alpha = 0.05$, statistical power $1 - \beta = 0.90$, conservative effect magnitude $f = 0.20$, and pre-post covariance coefficient $\rho \approx 0.50$ for a five-group instructional design. ANOVA, adjusted with ANCOVA, was used for analysis to account for the influence of covariates and avoid distortion of the results (1):

$$N \geq \frac{(1.96 + 1.28)^2 \times 0.50}{0.20^2} + 5 = 136.22,$$

The calculation yielded a minimum total allocation of approximately 136 learners, corresponding to about 27–28 participants per group in a balanced five-group design.

For pairwise comparisons, we further quantified the required group size using statistical power analysis to ensure that the results were truly robust (2). For $\alpha = 0.05$, power $1 - \beta = 0.90$ and a

medium standardized effect $d = 0.40$, the calculation yielded:

$$n \geq \frac{2(1.96 + 1.28)^2}{0.4^2} = 131.22.$$

Because multi-metric assessment, mediation analysis, and HCI/UX modelling require stable parameter estimation, the operational target was increased to 40 participants per group. The final empirical sample therefore comprised 200 students.

The eligible cohort was allocated to the five instructional conditions through controlled random assignment within the screened stratum. This preserved probabilistic group equivalence after eligibility filtering. Baseline diagnostics, ANCOVA adjustment, and repeated-measures modelling further controlled residual pre-intervention variance and reduced selection bias.

A priori power analysis used $\alpha = 0.05$, power = 0.90, Cohen's $f = 0.20$ for omnibus testing, $d = 0.40$ for pairwise contrasts, and an assumed pre-post correlation of $\rho \approx 0.50$. Standard normal critical values were $Z_{1-\alpha/2} = 1.96$ and $Z_{1-\beta} = 1.28$. The minimum allocation was approximately $N = 136$, while $N = 200$ was retained to improve variance stability, mediation identifiability, and HCI/UX estimation.

3.4. Research tools

The instrumental stack combined a priori power calibration, psychometrically grounded learning metrics, HCI/UX indicators, and inferential statistical models. This structure supported reproducible measurement of cognitive, behavioural, and interaction dynamics in Smart/AR environments. Standardized operational definitions were used to improve cross-condition comparability and variance interpretation.

1. Sample size determination

For a fixed-effects one-way ANOVA (G groups) with effect size f [19]:

$$N \geq \frac{(Z_{1-\alpha/2} + Z_{1-\beta})^2 (1 - \rho)}{f^2} + G, \quad (1)$$

where N – total sample size; G – number of groups; f – Cohen's effect size; $Z_{1-\alpha/2}$ – standard normal quantile for Type-I error α ; $Z_{1-\beta}$ – quantile for power $1 - \beta$; ρ – pre-test–post-test correlation (for ANCOVA gain-control).

For pairwise comparisons (pre–post within group) with standardized effect d [20]:

$$n \geq \frac{2(Z_{1-\alpha/2} + Z_{1-\beta})^2}{d^2}, \quad (2)$$

where n – required sample size per group; d – Cohen's d (standardized mean difference).

2. Evaluation metrics*:

Growth in knowledge levels — both in raw and normalized terms [21]:

$$\Delta L_i = S_i^{post} - S_i^{pre}, g_i = \frac{S_i^{post} - S_i^{pre}}{S_{max} - S_i^{pre}}, \quad (3)$$

where S_i^{pre} , S_i^{post} – pre/post-test scores of learner i ; S_{max} – maximum possible score; ΔL_i – absolute gain; g_i – normalized gain.

Index of retention of learned material [22]:

$$R_i = \frac{S_i^{delay} - S_i^{pre}}{S_i^{post} - S_i^{pre}}, \quad (4)$$

where S_i^{delay} – delayed post-test score; R_i – proportion of preserved learning.

Integrated score of participation and immersion [23]:

$$E_i = \sum_{k=1}^K w_k x_{ik}, \quad (5)$$

where x_{ik} – standardized item score k for learner i ; w_k – factor loading or weight; K – number of items; E_i – engagement/immersion index.

Mental load indicator [24]:

$$CL_i = \frac{1}{J} \sum_{j=1}^J y_{ij}, \quad (6)$$

where y_{ij} – Likert score on cognitive load item j ; J – number of items; CL_i – mean cognitive load.

System adaptability indicator [25]:

$$A_i = \frac{N_i^{adapt}}{N_i^{events}}, \quad (7)$$

where N_i^{adapt} – number of adaptive interventions for learner i ; N_i^{events} – total interaction events; A_i – adaptivity ratio.

Indicator of the strength of differences between groups [26]:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{s_p}, s_p = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}, \quad (8)$$

where $\bar{X}_g$ – mean in group g ; s_g^2 – variance; n_g – group size; s_p – pooled standard deviation; d – Cohen's effect size.

Internal consistency (Cronbach's α) [27]:

$$\alpha = \frac{K}{K - 1} \left(1 - \frac{\sum_{k=1}^K \sigma_k^2}{\sigma_T^2} \right), \quad (9)$$

where K – number of items; σ_k^2 – variance of item k ; σ_T^2 – variance of total test score; α – reliability coefficient.

3. Metrics reflecting user experience and interaction in the Smart+AR system*:

Level of success in completing the task [28]:

$$\eta_i = \frac{T^{baseline}}{T_i^{Smart+AR}}, \quad (10)$$

where $T^{baseline}$ – median time in control condition; $T_i^{Smart+AR}$ – time of learner i ; $\eta_i > 1$ – temporal efficiency gain.

Interaction error rate [29]:

$$ER_i = \frac{N_i^{err}}{N_i^{actions}}, \quad (11)$$

where N_i^{err} – erroneous UI actions; $N_i^{actions}$ – total actions; ER_i – HCI error ratio.

Overall usability and user experience score [30]:

$$UX_i = \frac{25}{K} \sum_{k=1}^K z_{ik}, \quad (12)$$

where z_{ik} – recoded usability item (1–5 Likert); K – items; UX_i – standardized usability index (approx. 0–100).

Metric of user interaction saturation with the system [31]:

$$ID_i = \frac{N_i^{UI}}{T_i^{session}}, \quad (13)$$

where N_i^{UI} – number of meaningful UI/AR interactions; $T_i^{session}$ – session duration; ID_i – interactions per time unit (UI intensity).

**All metrics are normalized within the range [0,1].*

Normalized values of 0.95–1.00 represented relative scaling rather than ceiling saturation. The achievement instrument retained item discrimination of 0.42–0.71 and difficulty of 0.38–0.82. Post-test distributions remained non-truncated, with $|skewness| < 0.65$, $|kurtosis| < 0.80$, and SD values of 5.2–6.0 in higher-performing groups. These diagnostics indicated preserved score dispersion near the upper performance range.

4. Statistical inference and modelling:

A general linear model based on ANCOVA was used to accurately assess the final results [32]:

$$Y_{ij} = \mu + \tau_{g(j)} + \beta X_{ij}^{pre} + \varepsilon_{ij}, \quad (14)$$

where Y_{ij} – post-test (or gain) for learner i in group j ; μ – grand mean; $\tau_{g(j)}$ – fixed effect of instructional condition; X_{ij}^{pre} – covariate (pre-test); β – regression coefficient; ε_{ij} – random error.

The changes over time were clearly shown through repeated measures analysed using a mixed model [33]:

$$Y_{it} = \mu + \tau_{g(i)} + \lambda_t + (\tau\lambda)_{g(i)t} + u_i + \varepsilon_{it}, \quad (15)$$

where Y_{it} – score of learner i at time t (pre-, post-, delayed); λ_t – time effect; $(\tau\lambda)_{g(i)t}$ – interaction “group $\times$ time”; u_i – random subject effect; ε_{it} – residual.

Mediation / structural equation model (Smart+AR $\rightarrow$ immersion $\rightarrow$ learning) [34]:

$$\begin{aligned} M_i &= aX_i + \varepsilon_{Mi}, \\ Y_i &= c'X_i + bM_i + \varepsilon_{Yi}, \end{aligned} \quad (16)$$

where X_i – binary/ordinal indicator of instructional condition; M_i – mediator (immersion or personalization index); Y_i – outcome (gain, retention); a , b , c' – path coefficients; ε_{Mi} , ε_{Yi} – error terms; indirect effect = ab .

Statistical processing was performed in Python using NumPy and Pandas for data handling, Matplotlib for figures, and SciPy and statsmodels for inference and effect estimation. This software stack supported reproducible calculation of descriptive statistics, ANCOVA, repeated-measures models, and mediation parameters.

4. RESULTS AND DISCUSSION

Initial eligibility was determined using a standardized screening test administered under identical conditions (Figure 2). The screening stage established the competence threshold required for the intervention and reduced uncontrolled floor effects. After selection, a separate domain-specific pre-test was used to verify experimental baseline equivalence across the five groups.

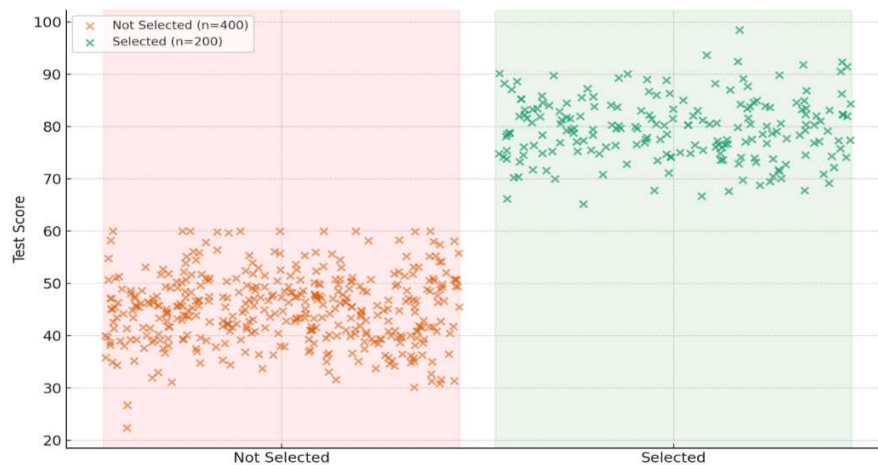


Figure 2: Distributional Segmentation of the Initial Screening Sample ($N = 600$) into Non-Eligible and Eligible Cohorts

Figure 2 separated 400 non-eligible candidates (66.7%; $M = 48.7$, $SD = 6.4$) from 200 eligible candidates (33.3%; $M = 81.9$, $SD = 5.8$) using the 65-point threshold. The selected cohort was then allocated equally across Groups A–E, with 40 students per condition. The screening score and the later domain-specific pre-test were distinct instruments; the latter produced an overall baseline

of 72.4 ± 6.1 . This separation preserved variance control without treating screening performance as the experimental outcome. Participation was voluntary, data were anonymized, and the design involved no invasive or risk-bearing procedures. Generalization was therefore restricted to learners meeting the predefined competence threshold.

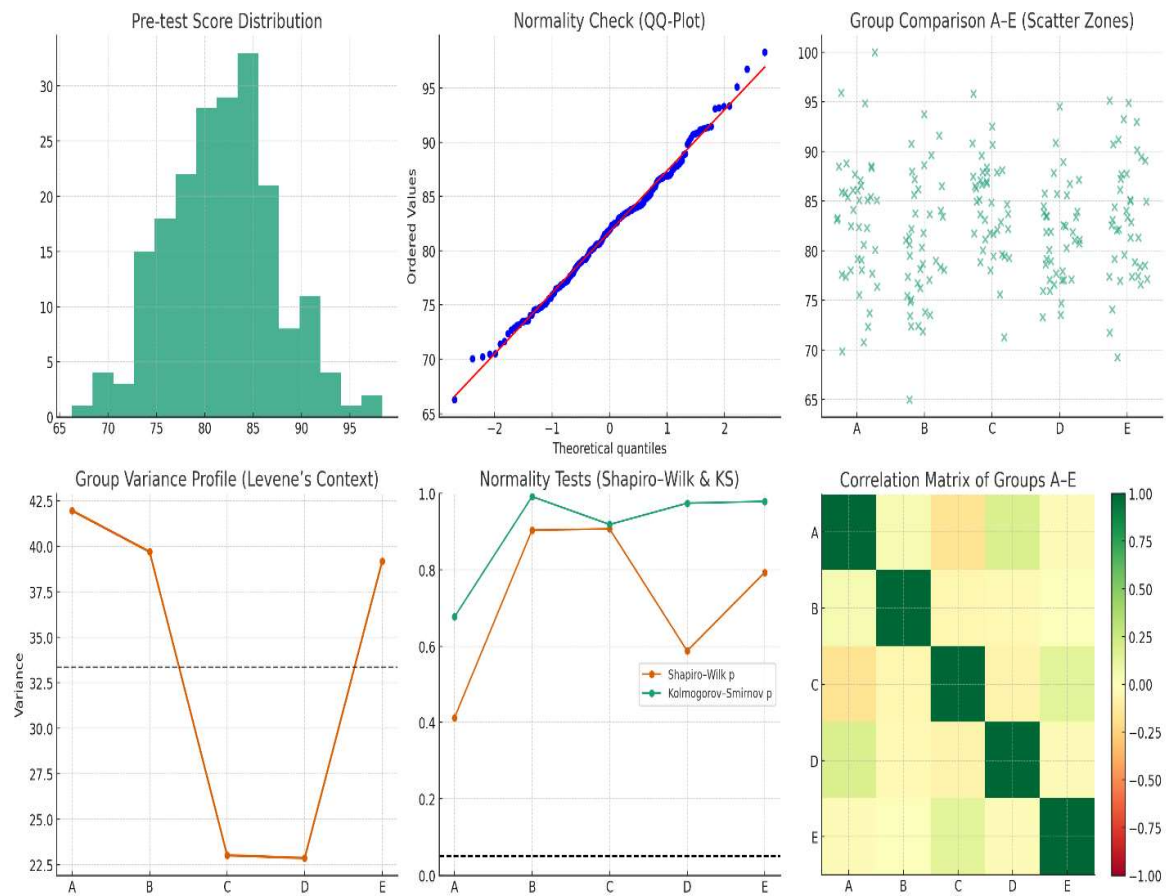


Figure 3: Comprehensive Pre-Experimental Diagnostics of the Student Sample Across Screening, Distributional, and Variance-Stability Metrics

Figure 3 assessed the stability of the screening-derived eligibility data and the consistency of group allocation. Screening-score distributions met normality requirements (Shapiro–Wilk $p > .18$), and variance homogeneity was retained (Levene $p = .72$). The subsequent domain-specific experimental baseline was assessed separately and also showed normality ($p > .12$), Levene $p = .41$, and inter-group deviation below 3.5%. These two diagnostic layers served different purposes and jointly supported baseline comparability.

All groups completed equivalent curricular units, instructional time, and assessment checkpoints. Only the intervention modality differed. This controlled exposure isolated the effects of AI adaptivity, visual augmentation, spatial audio, and multimodal integration before the metric-based comparison shown in Figure 4.

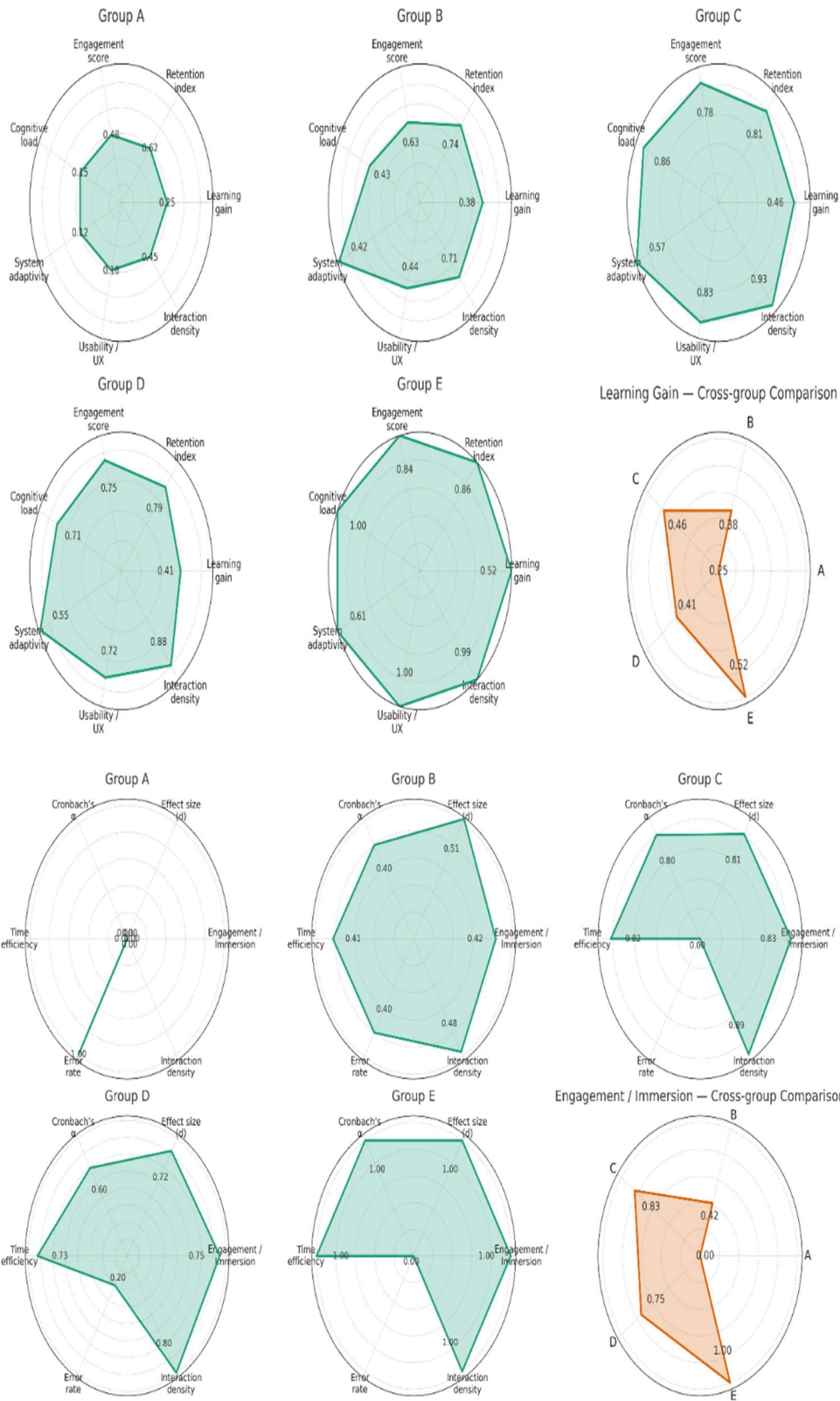


Figure 4: Metric-Based Evaluation of Controlled Instructional Intervention Across Five Intelligent Learning Conditions

Figure 4 showed a consistent modality gradient across cognitive, behavioural, and HCI/UX indicators. Group A remained lowest across most normalized measures. Group B improved adaptivity and feedback efficiency but showed limited immersion. Group C exceeded 0.80 on key visual-AR indicators, while Group D achieved strong retention and hands-free engagement. Group E produced the highest integrated profile, with several normalized indices approaching 0.95–1.00. The

pattern supported cumulative benefits from multimodal orchestration rather than a uniform effect of technology exposure.

The descriptive hierarchy justified formal inferential testing rather than interpretation from normalized profiles alone. ANCOVA adjusted post-test differences for baseline performance, repeated-measures models assessed temporal stability, and mediation analysis tested whether immersion transmitted part of the instructional effect (Figure 5).

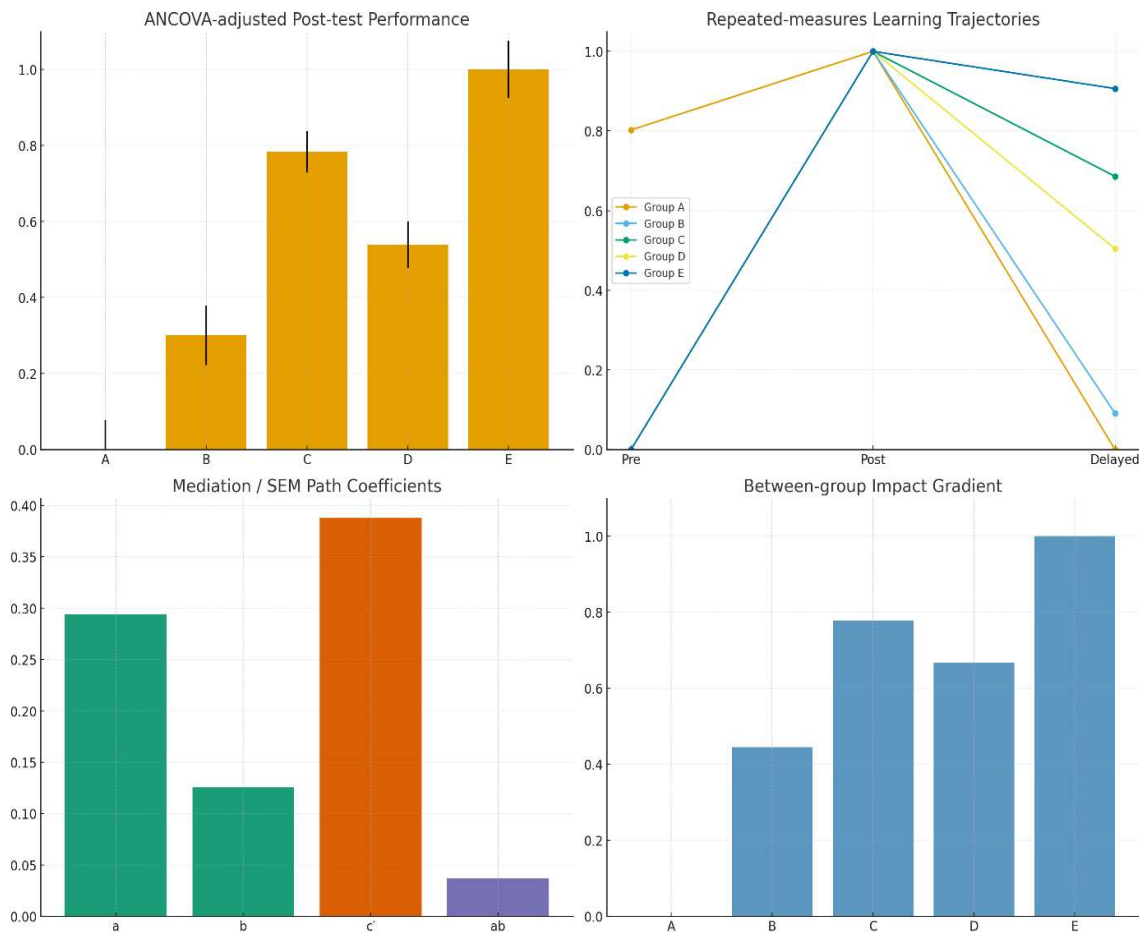


Figure 5: Statistical Verification of Intervention Effects Across ANCOVA, Repeated Measures Dynamics, Mediation Pathways, and Inter-Group Impact Gradients

Figure 5 confirmed statistically robust modality-specific effects. ANCOVA showed a significant group effect, $F(4,194) = 18.72$, $p < .001$, partial $\eta^2 = .278$. The time $\times$ condition interaction was also significant, $F(4,194) = 21.36$, $p < .001$, partial $\eta^2 = .306$. Mediation analysis produced $ab = 0.214$, $SE = 0.052$, 95% CI [0.118, 0.324], indicating that 22.4% of the total effect was mediated. Model assumptions were examined before inference. Regression-slope homogeneity was supported, $F(4,190) = 1.12$, $p = .35$; Mauchly's $W = 0.94$, $p = .21$ indicated no

material sphericity violation. The intra-class correlation remained below 0.03, supporting independence under the allocation design.

Table 2 reports untransformed means and standard deviations for each condition at pre-test, post-test, and delayed assessment. These raw values allow direct verification of the performance gradient, retention pattern, and normalized indices used in the analytical models.

Table 2: Raw Descriptive Statistics Across Five Instructional Conditions (Pre-test, Post-test, Delayed Retention)

Group	Condition	Pre-test M ± SD	Post-test M ± SD	Delayed Test M ± SD	Retention Δ (%)
A	Traditional	72.1 ± 6.3	75.4 ± 6.8	70.2 ± 7.1	-6.9
B	Smart (AI, 2D)	72.6 ± 6.0	82.8 ± 6.4	78.9 ± 6.7	-4.7
C	Smart + Visual AR	72.3 ± 5.9	88.7 ± 5.6	85.2 ± 5.9	-3.9
D	Smart + Audio AR	72.5 ± 6.2	86.9 ± 6.0	83.1 ± 6.4	-4.4
E	Smart + Hybrid AR	72.7 ± 6.1	92.4 ± 5.1	90.1 ± 5.4	-2.5

Pre-test distributions were equivalent across groups ($p > .12$; Levene $p = .41$). Post-test means ranged from 75.4 ± 6.8 in Group A to 92.4 ± 5.1 in Group E. Delayed means ranged from 70.2 ± 7.1 to

90.1 ± 5.4 , while retention decay decreased from -6.9% to -2.5% . These raw values corroborated the adjusted and normalized results without relying solely on transformed indicators.

The intervention effects were also observable in concrete instructional tasks. Visual AR supported anchored 3D process diagrams and technical-vocabulary mapping; audio AR provided location-sensitive prompts during hands-free information-processing tasks. The hybrid condition synchronized these cues during sequencing and terminology exercises. Comparable task structures were used at both institutions, allowing the observed effects to be interpreted across two educational contexts rather than one isolated classroom scenario.

The combined descriptive and inferential evidence supported the final stage: formulation of implementation recommendations linked directly to measured outcomes, statistical uncertainty, and identified operational risks (Table 3).

Table 3: Comprehensive Recommendations for Implementing Immersive Smart/AR Technologies in Education (developed by the authors).

Recommendation Point	Description of Recommendation	Academic & Metric-Based Justification	Implementation Risks & Mitigation Strategies	Roadmap (Effect- & Risk-Informed)
1. Hybrid Multimodal AR (Visual + Audio)	Integrate simultaneous visual AR overlays and spatial audio AR for dual-channel cognitive stimulation.	Group E achieved the highest post-test score (92.4 ± 5.1) and delayed score (90.1 ± 5.4). Retention decay was -2.5% , compared with -6.9% in the control condition.	Risk: Cognitive overload in low-literacy groups; device heterogeneity. Mitigation: Adaptive load control; standardized hardware; progressive onboarding.	Phase 1: pilot module (2–3 weeks). Phase 2: hybrid AR deployment in high-complexity instructional units. Phase 3: full-course integration after stable performance and retention are confirmed.
2. AI-Driven Adaptive Orchestration Layer	Embed AI modules controlling sequencing, pacing, and real-time feedback within Smart systems.	The mediation model was significant ($ab = 0.214$, $SE = 0.052$, 95% CI $[0.118, 0.324]$), with 22.4% of the total effect transmitted through the modeled mediating pathway.	Risk: Algorithmic bias and unstable personalization. Mitigation: periodic model retraining, bias auditing, and student-centered calibration loops.	Phase 1: Deploy learning-analytics dashboards. Phase 2: Integrate ML-based sequencing. Phase 3: Automate feedback cycles after monitoring variance stabilization.
3. Domain-Specific Visual AR (STEM-focused)	Deploy volumetric 3D models, dynamic overlays, and spatial simulations for complex conceptual content.	Group C reached 88.7 ± 5.6 at post-test and 85.2 ± 5.9 at delayed assessment, substantially exceeding the control condition while retaining score dispersion.	Risk: Content misalignment; high asset-production cost. Mitigation: Use modular AR templates; centralized asset repository; content-validation cycles.	Phase 1: Develop prototype 3D modules. Phase 2: Curriculum alignment. Phase 3: Scalable rollout to high-complexity courses.
4. Audio AR (u-Learning) for Mobile & Spatial Contexts	Use IR-localization & spatial audio cues for hands-free instruction in labs,	Group D reached 86.9 ± 6.0 at post-test and 83.1 ± 6.4 at delayed assessment,	Risk: Spatial interference; low hardware precision. Mitigation: Calibrate beamforming arrays;	Phase 1: Install localization infrastructure. Phase 2: Create audio-narrative

	museums, workshops.	supporting the effectiveness of spatial audio for sustained hands-free learning.	redundant IR/RGB tracking; noise-profiling.	modules. Phase 3: Scale to all applied-training spaces.
5. UX/HCI Optimization Protocols	Optimize Smart/AR interaction density, gesture design, and interface load.	Smart/AR conditions showed stronger normalized usability and interaction profiles than the control condition. UX/HCI effects were interpreted together with cognitive load and error-rate metrics rather than in isolation.	Risk: Over-complex interfaces; gesture misrecognition. Mitigation: Usability testing; iterative HCI prototyping; cross-device synchronization.	Phase 1: UX benchmarking. Phase 2: interface refinement. Phase 3: continuous usability monitoring with normalized UX ≥ 0.80 .
6. Phased Variance-Guided Deployment Strategy	Implement AR/Smart integration gradually using variance and stability thresholds.	The significant time $\times$ condition effect, $F(4,194) = 21.36$, $p < .001$, partial $\eta^2 = .306$, showed that intervention effects developed differently across measurement points.	Risk: Early-phase instability; insufficient student adaptation. Mitigation: Incremental exposure; blended instruction; variance-based pacing.	Phase 1: Small-scale pilot. Phase 2: Medium-scale rollout. Phase 3: Full institutional integration once variance < 0.20 .
7. Instructor AR-Pedagogical Competence Development	Train teachers in multimodal scenario design, AR asset integration, and adaptive pedagogical engineering.	Instructor procedures were standardized rather than modeled as an independent causal factor. Teacher competence is therefore treated as an implementation requirement requiring external validation.	Risk: Low digital competence; resistance to innovation. Mitigation: Structured AR-training curriculum; methodological support teams; certification programs.	Phase 1: Instructor training workshops. Phase 2: Co-teaching with AR specialists. Phase 3: Autonomous AR-based instruction.

The empirical results supported a multi-level Smart/AR model in which adaptivity, multimodal immersion, and HCI/UX jointly shaped learning outcomes. However, the observed hierarchy should be interpreted as conditional rather than universally technology-driven. The strongest effects occurred under standardized hardware, controlled exposure, trained instructors, and a screened competence range. These boundary conditions are essential when translating the findings beyond the experimental setting.

The findings were therefore compared critically with current research rather than treated as isolated confirmation. The comparison focused on where the present results converged with prior evidence, where they extended it through controlled inference, and where methodological differences prevented direct equivalence.

Sudharson et al. [35] emphasized AR-based visual simplification, while Singh et al. [36] focused on cognitive-load reduction in AI-supported simulations. The present findings agreed that representational support matters, but showed that hybrid multimodality produced the strongest adjusted outcomes. Direct numerical equivalence remains inappropriate because the studies used different tasks, scales, and exposure durations.

The reviews by Asitah et al. [37] and Al-Ansi et al. [38] documented rapid AR/VR expansion but offered limited causal evidence. The present controlled design addressed this limitation through baseline adjustment, repeated measurement, and mediation analysis. Nevertheless, its two-institution sample remains narrower than the heterogeneous evidence synthesized in those reviews.

Kaur and Kumar [39] examined immersive support for preparatory STEM activity, whereas Mondal [40] considered VR/AR/AI for information-literacy services. The present experiment extended these context-specific applications by comparing complete instructional architectures. However, transfer beyond technical communication and information-processing tasks still requires independent testing.

Tursunova et al. [41] and Rajamohan et al. [42] emphasized technological potential and ecosystem readiness. The present results showed that Smart/AR systems can produce measurable gains under calibrated infrastructure and controlled delivery. This does not remove deployment constraints; instead, it shows that hardware reliability, interoperability, and implementation fidelity are part of the causal environment.

Yambal and Waykar [43] and Judijanto et al. [44] highlighted equitable access, data governance, and instructor readiness. These concerns were controlled experimentally but not resolved institutionally. The study therefore established performance efficacy under specified conditions, while privacy, accessibility, algorithmic fairness, and teacher adaptation remain external validity requirements.

Overall, current literature supports the educational potential of AI, AR, and VR, but differs substantially in design rigor and outcome measurement. The present study strengthened causal interpretation through raw-score reporting, covariate adjustment, temporal analysis, and mediation modelling. Its results support hybrid Smart/AR as the strongest condition within this design, not as a universally superior solution. Baseline competence, modality preference, device access, and cognitive-load tolerance may moderate effectiveness in broader populations.

5. LIMITATION

The study was limited by its controlled setting, two-institution sample, 6–8-week intervention, and eligibility threshold that excluded lower-baseline learners. The design did not estimate cost-effectiveness, institutional privacy risk, algorithmic fairness, or independent instructor effects. Device calibration and standardized delivery may also exceed routine classroom conditions. Accordingly, external validity should be tested across broader populations, disciplines, institutions, and longer observation periods.

6. CONCLUSION

Findings. The study developed and tested a five-condition empirical framework for Smart/AR learning. The 200-student cohort showed baseline equivalence before intervention. Post-test performance increased from 75.4 ± 6.8 in traditional instruction to 92.4 ± 5.1 in hybrid Smart/AR. Delayed scores increased from 70.2 ± 7.1 to 90.1 ± 5.4 , while retention decay decreased from -6.9% to -2.5% . ANCOVA confirmed a large group effect, $F(4,194) = 18.72$, $p < .001$, partial $\eta^2 = .278$. The time $\times$ condition interaction was also large, $F(4,194) = 21.36$, $p < .001$, partial $\eta^2 = .306$. Mediation was significant, $ab = 0.214$, $SE = 0.052$, 95% CI [0.118, 0.324].

Research contribution. The study showed that Smart/AR effectiveness depended on the combined operation of adaptive sequencing, multimodal immersion, and HCI/UX quality. Its main contribution was a unified comparison of five instructional architectures using raw outcomes, normalized metrics, longitudinal testing, and mediation analysis. The resulting implementation framework specified performance ≥ 0.75 , adaptivity ≥ 0.40 , and normalized UX ≥ 0.80 as operational decision thresholds within the tested context.

Academic novelty. The research integrated large-scale screening, five-arm intervention testing, cognitive-behavioural-HCI measurement, and causal modelling within one analytical framework. It also distinguished screening competence from experimental baseline performance and linked multimodal architecture to delayed retention. This combination addressed the methodological fragmentation identified in the literature review.

Practical significance. The findings provide an evidence-based sequence for institutional Smart/AR adoption: establish baseline equivalence, calibrate the technical environment, deploy modality-specific interventions, monitor learning and HCI/UX metrics, and scale only after stability is demonstrated. The framework is intended for controlled educational implementation rather than unrestricted technology substitution.

Unresolved questions. It remains unclear whether the observed advantages persist beyond one academic term or transfer to students below the screening threshold. Further research should test whether the operational thresholds remain stable across disciplines, cultures, device ecosystems, and instructor profiles. The effects of privacy constraints, algorithmic bias, accessibility, and cost on large-scale implementation also remain open.

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