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A COMPARATIVE EXTENDED UTAUT ANALYSIS OF VIRTUAL REALITY AND AUGMENTED REALITY ADOPTION ACROSS INSTITUTIONAL DIVIDES

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ABSTRACT

This study explores educators' and learners' multifaceted perceptions across public and private educational institutions regarding the integration and adoption of virtual reality (VR) and augmented reality (AR) applications. Recognizing the paradigm shift toward Education 4.0, the study operationalizes an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework to isolate the predictive behavioral determinants of immersive technology adoption. Using a snowball sampling methodology, a structured psychometric instrument was administered to teachers across primary, secondary, and tertiary levels, as well as to secondary and tertiary students, yielding a robust sample of 1000 valid responses. Covariance-based Structural Equation Modeling (CB-SEM) and Confirmatory Factor Analysis (CFA) were conducted in IBM AMOS to evaluate the latent relationships among effort expectancy, performance expectancy, hedonic motivation, social influence, price value, habit, facilitating conditions, and the ultimate behavioral intention to adopt AR/VR platforms. The empirical findings establish that effort expectancy, performance expectancy, and hedonic motivation are universally significant drivers of adoption intent. Subsequent multi-group path analyses uncover profound demographic disparities; while students are heavily influenced by hedonic motivation and intrinsic enjoyment, educators base their adoption strategies strictly on performance metrics and are negatively impacted by rigid facilitating conditions. Furthermore, the public sector relies on habituation and performance expectancy to a greater extent than private institutions do. These critical insights provide actionable strategic intelligence for educational technologists, software developers, and academic policymakers seeking to minimize pedagogical friction and maximize the efficacy of extended reality deployments in modern classrooms.



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I. INTRODUCTION

The contemporary educational landscape is currently undergoing a profound systemic metamorphosis, driven by the rapid evolution and deployment of immersive digital technologies. As modern civilization transitions toward the ideals of Society 5.0, a human-centric framework in which cyberspace and physical space are highly integrated to address socio-economic challenges, the pedagogical strategies used to prepare the next generation of learners must evolve commensurately [1]. Education 4.0, the corresponding academic paradigm, emphasizes the critical need to cultivate twenty-first-century competencies, notably critical thinking, advanced problem-solving, and technological literacy [2]. Within this transformative context, extended reality (XR) technologies, predominantly Virtual Reality (VR) and Augmented Reality (AR), have emerged as formidable instructional tools capable of redefining the spatial and cognitive parameters of teaching and learning [3].

The global market for AR and VR in education reflects this aggressive trajectory, with industry valuations projected to surge from USD 3.8 billion in 2023 to an estimated USD 14.2 billion by 2028, representing a formidable Compound Annual Growth Rate (CAGR) of 29.6 percent [4]. Despite this exponential market expansion and the theoretical promise of immersive technologies, the practical, ubiquitous adoption of AR and VR within traditional classroom environments remains highly fragmented and inconsistent [5]. While advanced academic institutions and corporate training sectors have begun leveraging these tools for experiential learning, mainstream educational adoption is frequently impeded by a complex matrix of socio-technical barriers [4]. Extensive literature indicates that while VR and AR possess the theoretical capacity to vastly improve student engagement, spatial cognition, and the retention of highly complex, abstract information [6], the actual integration of these technologies into standardized curricula is stalled by inadequate infrastructure, prohibitive financial costs, and a fundamental lack of pedagogical alignment [7]. Furthermore, a significant geographical and economic bias exists within the current body of research; the overwhelming majority of empirical studies analyzing XR adoption have been conducted in Western, high-income demographics where digital infrastructure is ubiquitous and robustly funded [8].

This leaves a critical lacuna in the academic understanding of how these immersive platforms are perceived, evaluated, and ultimately adopted within developing educational ecosystems, particularly when contrasting the operational realities of government-funded public schools with those of privately funded institutions [9]. To address these profound gaps in the literature, this research initiates a comparative, socio-technical investigation into the dynamics of adoption for VR and AR educational applications. The primary problem this study seeks to address is the lack of a unified, empirically validated understanding of the psychological and environmental factors that drive or hinder the acceptance of immersive technologies across diverse educational stakeholders and institutional frameworks. To systematically deconstruct this problem, the investigation poses three central research questions. First, what are the fundamental structural relationships between the exogenous behavioral dimensions, specifically effort expectancy, performance expectancy, hedonic motivation, social influence, habit, price value, and facilitating conditions, and the endogenous behavioral intention to adopt virtual reality and augmented reality?

Second, does the systemic architecture of the academic institution, specifically the dichotomy between public and private funding models, generate statistically significant differences in how users adopt and integrate these technologies? Finally, do the psychological determinants of adoption differ significantly between the individuals tasked with deploying the technology (teachers) and those utilizing it for knowledge acquisition (students)? By anchoring this multidimensional inquiry in an extended iteration of the Unified Theory of Acceptance and Use of Technology (UTAUT2), this study transcends basic technological capability assessments to probe the deeply ingrained behavioral mechanics of end users. The hypothesis posits that differing institutional resources and fundamentally distinct user objectives (instruction versus comprehension) will fracture the homogenous adoption models previously recorded in corporate or leisure contexts. Ultimately, the findings derived from this robust structural equation modeling will provide crucial, actionable frameworks for instructional designers, institutional policymakers, and educational technology developers striving to bridge the digital divide and actualize the immersive potential of Education 4.0.

II. THEORETICAL REFERENCE

II.1 THE ONTOLOGICAL FRAMEWORK OF EXTENDED REALITY IN EDUCATION

The overarching taxonomy of Extended Reality (XR) encapsulates a diverse continuum of immersive technologies that manipulate human perception by blending physical realities with synthetic, computer-generated digital environments [3]. Within the educational sector, the two most prominent nodes on this reality-virtuality continuum are Virtual Reality (VR) and Augmented Reality (AR), each offering distinct cognitive affordances and pedagogical utilities.

II.1.1 *The Mechanics and Utility of Virtual Reality and Augmented Reality*

Virtual Reality is fundamentally defined as a medium composed of highly sophisticated computer simulations in which sensory feedback is continuously altered or augmented in response to the user's kinesthetic and spatial actions [8]. This continuous feedback loop induces a profound psychological state known as spatial presence, tricking the human cognitive architecture into feeling physically present or mentally immersed within a completely synthetic environment [10]. In contemporary educational settings, VR acts as a powerful experiential conduit. It liberates the learner from the geographical, temporal, and physical constraints of the traditional classroom, allowing students to embark on immersive virtual field trips to inaccessible locations, ranging from deep-space topographies to the microscopic interior of the human circulatory system [5]. The pedagogical efficacy of VR stems from its ability to facilitate high-fidelity experiential learning [7]. By immersing students in a controlled, risk-free virtual ecosystem, learners can conduct complex scientific experiments, practice hazardous engineering protocols, or develop intricate surgical techniques without the physical dangers or material costs of real-world failure [6]. Empirical investigations have consistently demonstrated that the spatial presence mechanisms inherent to VR significantly elevate baseline student engagement, improve long-term retention of scientific knowledge, and foster rapid development of practical psychomotor skills.²⁰

Furthermore, VR has demonstrated remarkable utility in clinical and psychological management; for instance, localized experiments utilizing VR interventions during pediatric vaccination procedures verified the technology's high efficiency in providing acute pain management and dramatic fear reduction, underscoring the deep cognitive overrides the technology can achieve [11]. In contrast to the total sensory isolation of VR, Augmented Reality integrates physical and digital information in real time, allowing users to remain visually and spatially grounded in their actual environment [8]. Utilizing technological formats such as smartphones, tablet computers, or specialized head-mounted displays, AR superimposes interactive, three-dimensional virtual assets such as data models, textual translations, or animations directly onto the user's perception of the physical world [6]. The integration of AR into educational frameworks radically enriches traditional pedagogical materials. Static interactive textbooks and physical field trips are transformed into dynamic, context-rich learning experiences that respond instantaneously to student inquiry [6]. The utility of AR is particularly pronounced in disciplines requiring complex spatial visualization and high-density data interpretation.

Complex, abstract datasets become physically tangible through AR visualizations, allowing students to interact with molecular structures or geometric theorems in three-dimensional space [6]. Additionally, language learners benefit immensely from AR applications that provide instantaneous, context-aware translations and real-time pronunciation guides overlaid onto physical texts or environments [6]. Research comparing the cognitive demands of AR and VR suggests that AR is frequently a more effective medium for conveying auditory and textual information, as it imposes a lower overall cognitive load than the fully immersive, sensory-heavy environments generated by VR [10]. Despite these profound advantages, meta-analyses reveal a critical systemic flaw in current AR adoption. The vast majority of research remains hyper-focused on the technical affordances of the software rather than exploring how AR can be deeply integrated into holistic pedagogical strategies to cultivate advanced cognitive skills, such as critical thinking [12].

II.1.2 The Evolution of Technology Acceptance Frameworks

The successful deployment of innovative educational technology is rarely determined solely by the software's technical superiority; rather, it is driven by the behavioral intent and psychological acceptance of the human end-user [11]. Historically, user acceptance evaluation was guided by the Technology Acceptance Model (TAM), a foundational theoretical framework that posited that an individual's behavioral intention to use a new system was primarily determined by two core variables: perceived usefulness and perceived ease of use [13]. While the TAM provided a robust initial architecture, the rapidly increasing complexity of consumer-facing technologies necessitated a more granular and encompassing psychological model [14]. To capture these multifaceted nuances, Venkatesh et al. (2012) synthesized decades of behavioral research to develop the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) [14]. The original UTAUT model consolidated prior theories into four primary dimensions: performance expectancy, effort expectancy, social influence, and facilitating conditions. The UTAUT2 extension explicitly tailored the framework for consumer and end-user contexts by incorporating three highly relevant subjective parameters: hedonic motivation, price value, and habit [14]. Given the consumer-grade nature of modern VR headsets and AR mobile applications, the UTAUT2 framework serves as the optimal theoretical anchor for this comparative investigation.

II.1.3 Operational Constructs of the UTAUT2 Model

The specific dimensions of the UTAUT2 model evaluated in this investigation are operationalized as follows. Performance Expectancy (PE) measures the degree to which an individual believes that using the immersive system will yield significant, tangible gains in academic performance, job efficiency, or learning outcomes. In the context of VR/AR, this reflects the user's belief that the technology will objectively make them a better student or a more effective educator. Effort Expectancy (EE) assesses the degree of cognitive and logistical ease associated with using the system, including the intuitiveness of the user interface, the physical comfort of the hardware, and the steepness of the learning curve required to operate the technology proficiently. Social Influence (SI) quantifies the extent to which an individual perceives those important others, such as academic peers, departmental superiors, or institutional administrators, believe they should actively use the new system, thereby capturing the normative social pressures driving technology adoption. Facilitating Conditions (FC) gauge the individual's perception of the objective support structures available to them, measuring whether the user believes the academic institution provides the necessary technical infrastructure, hardware availability, high-speed internet connectivity, and professional training required to seamlessly use VR and AR tools. Hedonic Motivation (HM), a critical addition in the UTAUT2 model, assesses the fun, intrinsic enjoyment, or psychological pleasure derived directly from using the technology, independent of its functional utility. Price Value (PV) represents the individual's internal cognitive trade-off between the perceived pedagogical benefits of XR applications and the monetary cost of acquiring and maintaining them. Habit evaluates the extent to which individuals tend to perform technology-related behaviors automatically, driven by prior experiential learning and repetitive, systemic integration. Finally, Behavioral Intention (BI) is the endogenous, dependent variable that represents the user's explicit psychological formulation and commitment to adopt and continuously use VR/AR applications in their educational routines.

II.1.4 Contextual Barriers and Institutional Disparities in Adoption

The empirical literature strongly suggests that the actual adoption of VR and AR in educational environments is far from homogeneous and is continually perturbed by severe systemic and demographic frictions. Educators, occupying the critical role of instructional designers, exhibit highly variable states of readiness. While many pioneer teachers recognize XR as a highly compelling platform capable of revolutionizing current teaching practices [13], their initial enthusiasm is often tempered by significant operational concerns. Teachers routinely report massive deficits in instructional design support, poor software interoperability across diverse hardware platforms, and a critical lack of targeted professional development required to align virtual content with rigid curriculum standards [15]. Furthermore, the macro-level diffusion of immersive technologies faces substantial economic, infrastructural, and ethical barriers. The sheer financial burden of outfitting classrooms with high-fidelity head-mounted displays, coupled with the necessity for robust, high-bandwidth technical infrastructure, presents a near-insurmountable hurdle for underfunded educational sectors [8].

Beyond hardware constraints, institutional adoption is hindered by the complexities of proprietary content development and deep-seated ethical concerns regarding student data privacy, regulatory compliance with frameworks such as GDPR and FERPA, and the safeguarding of sensitive biometric data collected by advanced eye-tracking VR headsets [8]. Additionally, unique physiological and psychological challenges exist, particularly concerning young learners. Prolonged immersion in VR can induce cybersickness, physical discomfort from poorly fitted hardware, and profound psychological disorientation—often referred to in the literature as "tricks of the mind"—in which extended exposure to synthetic environments momentarily alters the user's cognitive perception of physical reality [5]. Consequently, understanding how these multifaceted barriers distinctly impact resource-rich private institutions compared to government-funded public schools, and how they differentially influence educators' versus students' adoption mechanisms, is absolutely vital for the strategic, sustainable deployment of educational technology.

III. METHODS

III.1 RESEARCH PARADIGM AND SAMPLE SELECTION

To systematically deconstruct the behavioral determinants of immersive technology adoption, this research employed a quantitative, cross-sectional design utilizing structural equation modeling (SEM). Given the highly specific demographic requirements of the study, namely, the need to target individuals with at least a foundational awareness of, or baseline exposure to, VR and AR educational technologies, a snowball sampling methodology was strategically implemented. This non-probability sampling architecture involves utilizing an initial cohort of qualified participants to purposively recruit subsequent subjects from their respective professional and academic networks. In the context of evaluating emerging technologies where universal adoption has not yet occurred, snowball sampling is highly efficacious for maximizing reach across disparate geographical boundaries and institutional silos. The aggregate participant pool ($N=100$) was meticulously curated to encompass two primary operational cohorts: educators (teachers, $n=81$) and learners (students, $n=919$).

The educator cohort was deliberately drawn from across the primary, secondary, and tertiary academic spectrums to ensure a highly diverse range of pedagogical perspectives and technological readiness levels. Conversely, the student cohort was strictly restricted to secondary and tertiary educational levels. This methodological constraint was enforced under the psychological assumption that learners in these advanced cognitive developmental stages possess the requisite metacognitive maturity and self-awareness to accurately interpret and assess complex, abstract survey constructs, such as facilitating conditions and performance expectancy. Furthermore, to isolate the impact of socio-economic and institutional funding models, the sample was heavily stratified by institutional type, capturing vast datasets from both public/government-funded institutions ($n=633$) and privately funded educational institutions ($n=367$). The comprehensive demographic breakdown of the respondent sample, detailing role, gender, and institutional affiliation, is presented in Table 1.

Table 1: Demographic distribution of the study sample.

Category	Gender	Private (n=367)	Public (n=633)
Student (n=919)	Male	169	279
	Female	180	291
Teacher (n=81)	Male	5	20
	Female	13	43

Source: Authors, (2026).

III.2 DATA COLLECTION PROTOCOLS AND RIGOROUS SCREENING

The primary data acquisition phase was conducted using a highly efficient hybrid approach, combining supervised face-to-face questionnaire distribution and secure, encrypted online survey platforms. This dual-modality deployment ensured optimal response rates, minimized sampling bias, and guaranteed robust demographic diversity across the target populations. Following the closure of the data collection window, exactly 1000 valid, fully completed survey responses were retained for high-level inferential statistical analysis. Before engaging in complex structural modeling, the raw dataset underwent a battery of rigorous data screening protocols to ensure mathematical integrity. To detect and manage missing data points, Little's Missing Completely at Random (MCAR) statistical test was conducted. The output of this test yielded a probability value significantly greater than the stringent 0.05 alpha threshold ($MCAR > 0.05$).

This result mathematically confirmed that any missing values in the dataset were scattered entirely at random, assuring the researchers that the missingness did not introduce any systematic, confounding bias into the inferential models. Furthermore, to safeguard the covariant integrity of the structural models against the extreme distorting effects of multivariate anomalies, the Mahalanobis D-Squared (D^2) distance metric was computationally applied across the dataset. The Mahalanobis distance measures how many standard deviations a specific data point is from the mean of the multivariate distribution, accounting for the dataset's correlations. Cases exhibiting a severe anomaly probability ($p < .001$) were meticulously scrutinized and subsequently managed or excised to guarantee that profound outliers did not artificially inflate or skew the covariant relationships.

III.3 PSYCHOMETRIC INSTRUMENTATION

The survey instrument utilized for this study was meticulously operationalized based directly upon the validated psychometric constructs defined within the UTAUT2 framework by Venkatesh et al. (2012) [14]. The comprehensive measurement model was designed to evaluate eight distinct latent variables: Effort Expectancy (EE), Performance Expectancy (PE), Hedonic Motivation (HM), Social Influence (SI), Price Value (PV), Facilitating Conditions (FC), Habit, and the ultimate endogenous dependent variable, Behavioral Intention to Adopt (BI). The structured questionnaire comprised 24 highly specific, theoretically derived items engineered to accurately capture these latent psychological constructs. To quantify subjective responses, participants rated their alignment with each statement on a standardized 5-point Likert scale. The psychometric anchors ranged from 1 ("strongly disagree") to 5 ("strongly agree"), representing a universally validated and highly reliable scaling architecture for gauging precise levels of cognitive agreement in advanced behavioral and social science research [16].

III.4 ANALYTICAL ARCHITECTURE AND STATISTICAL MODELING

The high-level statistical analysis was executed utilizing IBM SPSS AMOS (Analysis of a Moment Structures) software, an industry-standard platform specifically engineered for executing complex Covariance-Based Structural Equation Modeling (CB-SEM). The analytical architecture proceeded through two distinct, sequential phases to ensure absolute scientific validity. In the initial phase, a rigorous Confirmatory Factor Analysis (CFA) was conducted to stress-test the theoretical measurement model.

The CFA evaluated the internal consistency, convergent validity, and discriminant validity of the utilized survey scales, mathematically ensuring that the theoretical behavioral constructs were accurately and exclusively represented by their designated indicator variables. The standard measurement model equation mapping an observed indicator x to its underlying latent construct ξ is expressed mathematically as:

$$x = \Lambda_x \xi + \delta \quad (1)$$

Where Λ_x represents the factor loading matrix (the strength of the relationship), ξ signifies the unobserved latent construct being measured, and δ denotes the inherent measurement error vector. Following validation of the measurement architecture, the second phase involved conducting a comprehensive structural path analysis. This phase computationally tested the complex web of hypothesized causal relationships flowing from the exogenous constructs toward the endogenous behavioral intention. Crucially, to uncover the targeted demographic and institutional nuances at the core of this investigation, a Multi-Group Analysis (MGA) was embedded into the SEM protocol. MGA is an advanced statistical technique that permits the simultaneous estimation of the entire theoretical model across different, mutually exclusive sub-populations, Public versus Private Institutions, and Students versus Teachers. By constraining and releasing specific parameters, the MGA determines whether the structural path coefficients (β) and, by extension, the fundamental psychological mechanisms of adoption differ significantly across demographic groups.

IV. RESULTS AND DISCUSSIONS

IV.1 CONSTRUCT RELIABILITY AND CONVERGENT VALIDITY

The integrity and scientific robustness of the measurement model were initially assessed through standard metrics of internal consistency and convergent validity. As explicitly detailed in Table 2, all latent variables within the model demonstrated exemplary, highly stable reliability metrics. The calculated Cronbach's alpha (α) values ranged from a baseline of 0.788 (Facilitating Conditions) to a peak of 0.926 (Hedonic Motivation), substantially exceeding the conventional psychometric acceptability threshold of 0.70. To further substantiate the structural stability of the constructs beyond simple inter-item correlation, the Composite Reliability (CR) and Average Variance Extracted (AVE) were computed. The CR values, which provide a more robust measure of internal consistency by accounting for varying factor loadings, universally surpassed the 0.60 operational benchmark, indicating exceptionally strong internal cohesion among the measurement items designated for each specific latent construct. Crucially, the Average Variance Extracted (AVE) for all eight variables exceeded the stringent, non-negotiable 0.50 threshold. The AVE mathematically quantifies the proportion of variance a latent construct captures from its specific indicators relative to the amount of variance due to measurement error. By exceeding 0.50, the data signifies that the latent constructs successfully explain more than half of the total variance present in their respective indicator variables, thereby confirming highly robust convergent validity across the entire theoretical model.

Table 2: Construct Reliability and Validity Indices.

Latent Construct	Cronbach's alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Hedonic Motivation (HM)	0.926	0.862	0.675
Habit	0.877	0.885	0.720
Effort Expectancy (EE)	0.885	0.918	0.788
Social Influence (SI)	0.917	0.854	0.661
Performance Expectancy (PE)	0.862	0.927	0.809
Price Value (PV)	0.848	0.882	0.714
Behavioral Intention (BI)	0.855	0.796	0.565
Facilitating Condition (FC)	0.788	0.855	0.664

Source: Authors, (2026).

IV.2 DISCRIMINANT VALIDITY AND ORTHOGONAL FACTOR ARCHITECTURE

Discriminant validity is an essential diagnostic criterion that ensures each theoretical construct is empirically distinct and statistically orthogonal to the others within the highly integrated model. This independence was rigorously verified utilizing the Fornell-Larcker criterion and a comprehensive examination of the construct correlation matrix, as presented in Table 3. According to this strict criterion, the diagonal values (which represent the square root of the AVE for each respective construct) must be strictly greater than any of the off-diagonal correlation coefficients located within the same corresponding rows and columns. The computational analysis confirmed this requirement without exception; the latent variables demonstrably share significantly more variance with their designated measurement indicators than they do with any other distinct construct in the UTAUT2 model. This confirms that the survey instrument successfully isolated distinct psychological domains without operational cross-contamination.

Table 3: Discriminant validity of measures utilizing the Fornell-Larcker criterion.

Construct	HM	Habit	EE	SI	PE	PV	BI	FC
HM	0.899							
Habit	0.249***	0.845						
EE	0.556***	0.584***	0.849					
SI	0.442***	0.754***	0.725***	0.888				
PE	0.624***	0.523***	0.771***	0.645***	0.822			
PV	0.457***	0.811***	0.591***	0.700***	0.604***	0.815		
BI	0.647***	0.536***	0.861***	0.673***	0.759***	0.565***	0.813	
FC	0.511***	0.754***	0.661***	0.752***	0.740***	0.759***	0.623***	0.752

(Note: Diagonal values in bold represent the square root of AVE. *** indicates significance at $p < 0.001$)

Source: Authors, (2026).

Furthermore, the Confirmatory Factor Analysis yielded a rotated factor matrix with exceptionally clean item loadings. Table 4 displays the standardized factor loadings parsed across the eight distinct structural components. High primary loadings (generally scaling > 0.70) combined with minimal, negligible cross-loadings underscore that the individual scale items are correctly and powerfully aligned with their intended theoretical dimensions. For example, analyzing the first component, the survey items theoretically associated with Hedonic Motivation (HM1, HM2, HM3) loaded massively onto Component 1 (0.939, 0.931, and 0.929, respectively), while simultaneously exhibiting near-zero or negative influence on all other structural components. This structural precision affirms the absolute purity of the psychological measurement and validates the instrument's deployment.

Table 4: Factor Matrix demonstrating specific item loadings across all eight components.

Constructs	1	2	3	4	5	6	7	8
HM1	.939	-.060	-.019	.034	.003	-.010	-.077	.084
HM2	.931	-.005	-.008	.019	.033	.002	.011	-.035
HM3	.929	.052	-.017	-.061	-.008	-.010	.064	-.011
Habit2	-.033	.993	-.076	.003	.010	-.052	.002	.005
Habit1	-.039	.898	.009	-.081	.043	.088	.007	-.005
Habit3	.122	.707	.171	.117	-.145	-.026	.056	-.019
EE3	-.026	.069	.952	-.040	.100	-.056	-.111	.002
EE2	-.039	-.065	.841	.028	-.082	.069	.143	.006
EE4	.023	.000	.822	.024	.092	.000	.007	-.042
SI2	-.026	-.028	.032	.933	-.031	.002	.034	.014
SI1	-.029	.013	-.047	.928	-.002	.042	.047	-.029
SI3	.053	.021	.022	.879	.054	-.025	-.070	.016
PE1	-.048	-.066	.108	-.047	.882	-.013	.011	.046
PE3	.012	-.044	-.012	.018	.806	.064	.029	.061
PE4	.099	.103	-.008	.055	.791	-.044	.062	-.101
PV1	-.058	-.119	.019	.005	-.009	.993	-.023	-.017
PV2	.030	.108	-.017	-.021	-.029	.751	.101	.053
PV3	.057	.195	-.018	.045	.057	.718	-.082	-.025
BI1	-.005	.009	-.076	-.013	.094	.021	.896	-.020
BI2	-.007	.036	.019	.023	.013	-.046	.843	.062
BI3	.036	-.038	.369	.019	-.058	.008	.579	.020
FC3	-.003	-.003	-.149	-.016	.006	-.028	.176	.918
FC4	.156	-.096	.160	-.033	-.028	.043	-.093	.791
FC1	-.139	.283	.024	.104	.071	-.009	-.124	.623

Source: Authors, (2026).

IV.3 MODEL FIT ANALYSIS AND STRUCTURAL VALIDATION

Prior to interpreting the causal pathways and demographic divergence, the overall fitness of the structural equation model was rigorously evaluated. This step is critical to guarantee that the hypothesized theoretical network of relationships adequately and proportionally matched the actual empirical data covariance matrix generated by the field survey. As tabulated in Table 5, the model fit indices unambiguously satisfy all established absolute and incremental statistical fit thresholds. The relative Chi-square ratio (CMIN/DF) resulted in an estimate of 2.745. By falling perfectly within the optimal, highly restrictive target range of 1.0 to 3.0, this metric indicates that the model is neither over-parameterized nor excessively rigid. The Comparative Fit Index (CFI), which assesses model fit by comparing the data to the hypothesized model while adjusting for sample size, achieved a robust 0.971, comfortably exceeding the standard 0.95 cutoff for exceptional model fit. Furthermore, the critical error metrics, encompassing the Standardized Root Mean Square Residual (SRMR = 0.052) and the Root Mean Square Error of Approximation (RMSEA = 0.024), both remained well below their strict respective rejection thresholds of 0.08 and 0.06. The PClose value of 1 (which acts as a definitive statistical safeguard by testing the null hypothesis that RMSEA is ≤ 0.05) confirms with absolute certainty that the RMSEA is not significantly greater than zero. Collectively, these highly favorable parameters certify the structural model as an outstanding, mathematically sound framework for subsequent predictive hypothesis testing and multi-group extrapolation.

Table 5: Model Fit Measures for the Structural Equation Model.

Measure	Estimate	Threshold	Interpretation
CMIN	2459.452	--	--
DF	896	--	--
CMIN/DF	2.745	Between 1 and 3	Excellent
CFI	0.971	> 0.95	Excellent
SRMR	0.052	< 0.08	Excellent
RMSEA	0.024	< 0.06	Excellent
PClose	1	> 0.05	Excellent

Source: Authors, (2026).

IV.4 MULTI-GROUP PATH ANALYSIS: THE DICHOTOMY OF PUBLIC VS. PRIVATE INSTITUTIONS

A critical, highly novel facet of this investigation was to determine if macro-level institutional funding structures generate systemic variances in the psychological mechanisms driving VR/AR adoption among their respective populations. A Multi-Group Analysis was conducted to compare the unstandardized beta coefficients (β), critical ratios ($t/C.R.$), and probability values (p) explicitly between Private and Public academic institutions; the results are documented in Table 6.

Table 6: Path Analysis and Significant Differences Between Private and Public Institutions.

Path of Constructs			Private Schools			Public Schools			Significant Difference
Endogenous Variable		Exogenous Variable	β	t	p	β	$C.R.$	p	p
VR/AR Adoption	<-	Performance Expectancy	0.071	0.730	0.466	0.164	3.014	0.003	***
VR/AR Adoption	<--	Effort Expectancy	0.636	6.846	***	0.589	11.319	***	***
VR/AR Adoption	<--	Social Influence	-0.011	-0.112	0.911	0.054	1.139	0.255	0.969
VR/AR Adoption	<--	Facilitating Condition	0.085	0.631	0.528	-0.112	-1.742	0.082	0.920
VR/AR Adoption	<--	Hedonic Motivation	0.221	3.318	***	0.243	7.001	***	***
VR/AR Adoption	<--	Habit	0.103	0.901	0.368	0.136	2.141	0.032	***
VR/AR Adoption	<--	Price Value	-0.104	-1.076	0.282	-0.055	-1.016	0.310	0.150

(Note: *** indicates significance at $p < 0.001$)

Source: Authors, (2026).

The comparative data yield profound, multi-layered insights into the socio-economic realities of technology adoption. Within private educational institutions, the structural model simplifies considerably: only Effort Expectancy ($\beta = 0.636$, $p < .001$) and Hedonic Motivation ($\beta = 0.221$, $p < .001$) exert a statistically significant positive impact on the behavioral intention to adopt VR and AR. The exceptionally high sensitivity to Effort Expectancy suggests that users embedded in well-resourced private institutions—who likely already possess seamless access to a wide array of advanced digital tools—highly prioritize the intuitive nature and user-friendliness of immersive systems. If a VR or AR tool is clunky or difficult to use, the private-sector user, driven by high expectations for digital seamlessness, will reject it. They adopt the technology primarily because it is easy to use and intrinsically enjoyable (Hedonic Motivation). Conversely, the behavioral model governing public institutions manifests a far more complex, outcome-driven adoption matrix. In the public sector, Performance Expectancy ($\beta = 0.164$, $p < .003$), Effort Expectancy ($\beta = 0.589$, $p < .001$), Hedonic Motivation ($\beta = 0.243$, $p < .001$), and Habit ($\beta = 0.136$, $p < .032$) all exhibit significant, positive causal relationships with the intention to adopt.

The multi-group difference test mathematically confirms that the variance in behavioral parameters between the two institutional types is statistically significant across Performance Expectancy, Effort Expectancy, Hedonic Motivation, and Habit. The emergence of Performance Expectancy and Habit as significant drivers exclusively within public institutions indicates a starkly different operational reality. Users in public, government-funded environments, which often face resource constraints and highly rigid, standardized testing mandates, are heavily focused on the technology's utilitarian, grade-enhancing outcomes. They adopt VR/AR not just because it is novel or easy, but because they believe it will objectively improve their academic performance [14]. Furthermore, the reliance on Habit suggests that public school adoption requires systemic, repetitive integration into daily routines to become sticky, rather than relying on spontaneous, pleasure-driven usage.

Interestingly, Social Influence, Facilitating Conditions, and Price Value did not reach statistical significance across both demographic groups. The failure of Facilitating Conditions to dictate adoption intent implies that contemporary users, who are largely comprised of digital natives, possess a baseline intrinsic technological self-efficacy that overrides institutional infrastructural deficits; alternatively, it suggests that both sectors struggle equally to provide adequate technical support, rendering the variable a non-factor in individual decision-making [12]. Furthermore, the profound non-significance of Social Influence in Private ($\beta = -0.011$) and in Public ($\beta = 0.054$) is a telling indicator of market maturity. It implies that the decision to adopt immersive educational technology is highly individualized rather than peer-driven; students and teachers are no longer adopting XR simply because their peers are, but rather evaluating it purely on its personal utility and usability.

IV.5 MULTI-GROUP PATH ANALYSIS: THE PSYCHOLOGICAL GAP BETWEEN STUDENTS AND TEACHERS

To further dissect the structural parameters governing adoption, the dataset was bifurcated by stakeholder role, directly contrasting the psychological determinants of learners (Students) against those of instructional designers (Teachers). The analytical output of this comparison, detailed in Table 7, reveals the most striking behavioral divergence within the entire study.

Table 7: Path Analysis and Significant Differences Between Students and Teachers.

Path of Constructs			Students			Teachers			Significant Difference
Endogenous Variable		Exogenous Variable	β	t	p	β	$C.R.$	p	p
VR/AR Adoption	<--	Performance Expectancy	0.131	2.233	0.026	0.509	2.563	0.010	***
VR/AR Adoption	<--	Effort Expectancy	0.595	10.741	***	0.544	2.928	0.003	***
VR/AR Adoption	<--	Social Influence	0.065	1.288	0.198	-0.143	-0.921	0.357	0.127
VR/AR Adoption	<--	Facilitating Condition	-0.071	-1.015	0.310	-0.428	-2.051	0.040	0.00
VR/AR Adoption	<--	Hedonic Motivation	0.249	6.745	***	0.049	0.404	0.686	***
VR/AR Adoption	<--	Habit	0.138	2.002	0.045	0.299	1.600	0.110	***
VR/AR Adoption	<--	Price Value	-0.087	-1.444	0.149	0.130	0.964	0.335	0.065

Source: Authors, (2026).

For the student cohort, the structural modeling mirrors the broader trend toward highly inclusive public institutions. Student adoption of VR and AR technologies is strongly and positively predicated upon Performance Expectancy ($\beta = 0.131$, $p < .026$), Effort Expectancy ($\beta = 0.595$, $p < .001$), Hedonic Motivation ($\beta = 0.249$, $p < .001$), and Habit ($\beta = 0.138$, $p < .045$). The data unequivocally demonstrate that for a student to internalize and adopt immersive learning tools, they must perceive the technology as not only cognitively manageable (Effort Expectancy) and academically beneficial (Performance Expectancy), but also as absolutely critical: the experience must be intrinsically engaging and enjoyable (Hedonic Motivation) [17].

The immense significance of Hedonic Motivation confirms earlier literature postulations that digital-native learners respond exceptionally well to "gamified" or experientially stimulating platforms, validating VR's core utility in increasing spatial presence, psychological flow, and deep academic engagement [10]. In sharp, almost oppositional contrast, the educator cohort (teachers) operates under a distinctly divergent set of technological imperatives. For teachers, the dominant predictors of adoption are Performance Expectancy ($\beta = 0.509, p < .001$), Effort Expectancy ($\beta = 0.544, p < .003$), and, uniquely, Facilitating Conditions ($\beta = 0.428, p < .040$). Notably, Hedonic motivation holds absolutely no significant bearing on a teacher's intention to use VR/AR in their classroom ($\beta = 0.049, p < .686$). This indicates a highly pragmatic, outcome-oriented, and severely stressed approach to pedagogical design. Teachers evaluate immersive technology strictly through a lens of unyielding utility, whether the XR platform will objectively enhance the delivery of mandatory curriculum content (Performance Expectancy) and whether it is realistically deployable within a fifty-minute class period without overwhelming pedagogical friction or technical failure (Effort Expectancy). The fun or novelty of the hardware is entirely irrelevant to their operational calculus.

The significant, albeit intensely negative, impact of Facilitating Conditions among teachers ($\beta = -0.428$) is perhaps the most profound and concerning finding of this entire investigation. In traditional UTAUT modeling, better facilitating conditions generally drive higher adoption [14]. However, this inverse relationship suggests that as current institutional infrastructures or top-down systemic mandates increase, teacher willingness to adopt XR declines rapidly. This anomaly highlights severe issues of technological fatigue, overly restrictive administrative protocols, or a critical lack of autonomy in curriculum design. It starkly corroborates recent literature detailing the severe challenges and anxieties teachers face when attempting to integrate highly complex [18], unpredictable technologies into rigid, high-stakes classroom frameworks without adequate contextual training [15]. When administrators force "facilitating conditions" via mandates without providing actual pedagogical support, teachers actively resist adoption. The multi-group analysis ultimately confirms that the variance across all aforementioned primary constructs (Performance Expectancy, Effort Expectancy, Hedonic Motivation, Habit, and Facilitating Conditions) is highly statistically significant between educators and learners, proving that a one-size-fits-all deployment strategy for educational XR is fundamentally doomed to fail.

IV.6 SYNTHESIS OF CORE FINDINGS AND THEORETICAL IMPLICATIONS

The systematic aggregation of these multi-group results significantly extends the traditional boundaries and assumptions of the UTAUT2 framework when applied within a modern educational context [14]. Historically, theoretical adoption models assume a relatively homogeneous level of user intent, treating an organization as a single adopting entity. However, this empirical data unequivocally fractures that assumption, proving beyond doubt that the intent to adopt XR is deeply segmented by both functional role (teacher vs. student) and environmental constraint (public vs. private). Universally, Effort Expectancy emerged as the most resilient, dominant, and ubiquitous predictor of adoption intent across all four analyzed sub-populations. This fundamental reality dictates an unyielding law for educational technologists: despite the hyper-advanced, visually stunning nature of immersive reality, the primary barrier to entry remains basic usability [13]. If the VR hardware is cumbersome to wear, or if the AR software interface requires complex recalibration, neither the student's desire for immersive engagement nor the teacher's drive for instructional efficacy will compensate for the resulting cognitive overload and frustration. The technology must simply work seamlessly. Furthermore, the complete collapse of Social Influence as a predictive variable across all groups marks a definitive departure from early-stage technological innovations (where peer pressure heavily drives initial uptake), indicating that AR and VR in education have transcended the hype cycle and transitioned into a mature evaluation phase governed primarily by individualized, utilitarian, and ergonomic assessment.

V. CONCLUSIONS

This exhaustive empirical investigation systematically examined the multidimensional psychological and environmental perceptions surrounding the adoption of virtual reality (VR) and augmented reality (AR) among teachers and students in both public and private educational institutions. Utilizing a rigorously validated extension of the UTAUT2 framework, the study generated highly nuanced, statistically significant intelligence regarding the operational psychology of educational technology integration in the era of Education 4.0. The foremost conclusion drawn from the complex path analysis is that Effort Expectancy, Performance Expectancy, and Hedonic Motivation are the paramount, universal drivers facilitating the adoption of immersive technologies. However, deep cross-demographic analyses exposed profound systemic dichotomies that mandate highly targeted deployment strategies. In both private and public academic institutions, Effort Expectancy and Hedonic Motivation dictate the baseline parameters for student adoption; learners overwhelmingly prioritize frictionless ease of use and deep experiential enjoyment. Conversely, educators adopt a strictly utilitarian, pragmatic operational framework. Teachers are structurally indifferent to the hedonic or entertaining facets of VR/AR, grounding their adoption intent exclusively in Performance Expectancy (the tangible, measurable pedagogical benefits) and Effort Expectancy (the logistical ease of classroom deployment).

Moreover, the analytical output challenges several established industry assumptions. The consistent statistical insignificance of Social Influence and Price Value across the broader models suggests that adoption is now an individualized, pragmatic calculation not influenced by social normative pressures or immediate financial concerns (which are likely abstracted to the institutional level). Crucially, the data underscores a critical vulnerability in the educational supply chain: the negative correlation between facilitating conditions and teacher adoption. Because these technologies are rapidly emerging and market demand is surging toward a \$14.2 billion valuation, institutions risk catastrophic implementation failure if they impose top-down hardware mandates without aggressively enhancing pedagogical support capabilities tailored specifically for teachers. Without strategic alignment that emphasizes career readiness, seamless integration, and minimized pedagogical friction, teacher-led adoption will stagnate, rendering the technology useless regardless of student enthusiasm. Despite the robust methodological framework deployed herein, this research acknowledges several operational limitations that warrant future scientific inquiry. The sample size, while statistically massive and highly valid, represents a cross-sectional snapshot obtained within a limited temporal window; it captures immediate perceptual states rather than evolving, long-term adoption dynamics. It is highly recommended that future scholars execute extended longitudinal methodologies to firmly establish and confirm the causal evolution of these behavioral effects over prolonged, multi-year exposure periods.

Finally, given the localized nature of the snowball sampling methodology, future research must deliberately incorporate cross-cultural variables and socio-economic indicators unique to differing global societal architectures to definitively identify the universal relevance, adaptability, and ultimate scalability of this proposed immersive technology adoption model.

VI. AUTHOR'S CONTRIBUTION

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VIII. REFERENCES

- [1] M. Fukuyama, "Society 5.0: Aiming for a New Human-Centered Society," *Japan Spotlight*, vol. 27, pp. 47–50, Jul./Aug. 2018.
- [2] C. Fadel, M. Bialik, and B. Trilling, *Four-Dimensional Education: The Competencies Learners Need to Succeed*. Boston, MA: Center for Curriculum Redesign, 2015.
- [3] G. Lampropoulos, E. Barkoukis, K. Burden, and T. Anastasiadis, "Augmented Reality and Virtual Reality in Education: Public Perspectives, Sentiments, Attitudes, and Discourses," *Education Sciences*, vol. 12, no. 11, Art. no. 798, Nov. 2022. DOI: 10.3390/educsci12110798
- [4] MarketsandMarkets, "Augmented and Virtual Reality in Education Market – Global Forecast to 2028," MarketsandMarkets Research, 2023. [Online]. Available: <https://www.marketsandmarkets.com/Market-Reports/augmented-reality-in-education-market-203811025.html>
- [5] B. D. Boyles, "Virtual Reality and Augmented Reality in Education," in *Instructional Systems Design and the Diffusion and Adoption of Technology*, vol. 1. Norfolk, VA: Old Dominion University, 2017, ch. 4.
- [6] A. Radianti, T. A. Majchrzak, J. Fromm, and I. Wohlgenannt, "A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda," *Computers & Education*, vol. 147, Art. no. 103778, 2020. DOI: 10.1016/j.compedu.2019.103778
- [7] M. Akçayır and G. Akçayır, "Advantages and challenges associated with augmented reality for education: A systematic review of the literature," *Educational Research Review*, vol. 20, pp. 1–11, 2017. DOI: 10.1016/j.edurev.2016.11.002
- [8] M. Ghobadi, S. Shirowzhan, M. M. Ghiai, F. M. Ebrahimzadeh, and F. Tahmasebinia, "Augmented Reality Applications in Education and Examining Key Factors Affecting the Users' Behaviors," *Education Sciences*, vol. 13, no. 1, Art. no. 10, Jan. 2023. DOI: 10.3390/educsci13010010
- [9] M. C. Bautista, I. R. Evangelista, A. Culaba, R. S. Concepcion, and E. P. Dadios, "Technology Adoption of Augmented and Virtual Reality in a Progressive Philippines: A Socio-techno-economical Analysis," in *Proc. 2022 IEEE 14th Int. Conf. Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, Boracay Island, Philippines, 2022, pp. 1–6. DOI: 10.1109/HNICEM57413.2022.10109429
- [10] C. Moro, Z. Štromberga, A. Raikos, and A. Stirling, "Augmented Versus Virtual Reality in Education: An Exploratory Study Examining Science Knowledge Retention When Using Augmented Reality/Virtual Reality Mobile Applications," *Cyberpsychology, Behavior, and Social Networking*, vol. 20, no. 11, pp. 645–651, 2017. DOI: 10.1089/cyber.2017.0205
- [11] S. Alshammari, "An Extended UTAUT2 Model to Explain the Adoption of Virtual Reality Technology in Health Centers: An Empirical Study Based in Riyadh," *Int. J. Computer Science and Network Security*, vol. 21, no. 3, pp. 204–216, Mar. 2021.
- [12] J. Garzón, J. Pavón, and S. Baldiris, "Systematic review and meta-analysis of augmented reality in educational settings," *Virtual Reality*, vol. 23, no. 4, pp. 447–459, 2019. DOI: 10.1007/s10055-019-00379-9
- [13] R. Y. Syed Far, A. M. Sharif, M. D. A. Halim, and S. N. A. Syed, "Identifying Factors Affecting Acceptance of Virtual Reality in Classrooms Based on Technology Acceptance Model (TAM)," *Asian Journal of University Education*, vol. 15, no. 3, pp. 51–60, Dec. 2019. DOI: 10.24191/ajue.v15i3.7845
- [14] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS Quarterly*, vol. 36, no. 1, pp. 157–178, Mar. 2012. DOI: 10.2307/41410412
- [15] R. Videla, C. Aguayo, R. Veloz, and M. Rossel, "Introducing Virtual Reality and Emerging Technologies in a Teacher Training STEM Course," *Education Sciences*, vol. 13, no. 10, Art. no. 1044, Oct. 2023. DOI: 10.3390/educsci13101044
- [16] W. M. Vagias, "Likert-Type Scale Response Anchors," Clemson International Institute for Tourism & Research Development, Clemson University, 2006.
- [17] E. Ibili, D. Resnyansky, and M. Billingham, "Adoption of Augmented Reality Technology by University Students," *Technology, Knowledge and Learning*, vol. 24, no. 3, pp. 341–366, 2019. DOI: 10.1007/s10758-018-9359-2
- [18] F. N. Ofosu-Amaah, "Diffusion of Virtual and Augmented Reality in Pre-K to 12 Education: Experiences and Perceptions of Pioneer Teachers," Ed.D. dissertation, Seton Hall University, South Orange, NJ, 2021.