

AI-Based Learning Environments and Their Impact on Academic Success: The Mediating Role of Engagement and Instructional Design

Samina Rafique¹, Ans Elahi², Ruqia Bibi³, Muhammad Arfaq⁴, Naeem Akhtar⁵

¹Lecturer, Department of Education Women University of Bagh AJK, samina.rafique85@yahoo.com

²PhD Scholar, My University Faculty of education Islamabad, JSET Qandeel School Kohati Bazaar Rawalpindi.

³PhD Scholar, Al Hamd Islamic University Islamabad, scholarruqia@gmail.com

⁴Ph.D. Scholar, Muslim Youth University, Islamabad, arfaqdj@gmail.com

⁵PhD Scholar, My University, Assistant Professor, IMCB, F-8/4 Islamabad, dedu241002@myu.edu.pk

DOI: <https://doi.org/10.70670/sra.v4i2.2039>

Abstract

This study investigates AI-based learning environments and their influence on the academic success of Grade 12 Biology students at Islamabad Model College for Boys, F-10/3 (IMCB F-10/3), Islamabad, Pakistan, with specific attention to the mediating roles of student engagement and instructional design quality. Utilizing a quasi-experimental pretest-posttest control group design, a stratified random sample of N = 80 Grade 12 Biology students was drawn from the institution's four sections and assigned to experimental (n = 40) and control (n = 40) conditions. The experimental group received Biology instruction delivered within AI-enhanced learning environments—incorporating adaptive learning platforms, intelligent feedback systems, and AI-powered content visualization—structured through principled instructional design frameworks (ADDIE and UDL). Standardized data collection instruments included the Academic Success Assessment (ASA), the Multidimensional Student Engagement Scale (MSES), and the Instructional Design Quality Rating (IDQR). Statistical analyses comprised independent samples t-tests, paired samples t-tests, one-way ANOVA, and Pearson correlation with mediation analysis. Findings demonstrated statistically significant academic success gains in the experimental group ($t(78) = 5.12, p < .001, d = 1.14$) and confirmed that student engagement ($\beta = .43, p < .001$) and instructional design quality ($\beta = .37, p < .001$) jointly and significantly mediated the relationship between AI-based learning environments and academic success. The study concludes that AI-based environments, when structured through deliberate instructional design and leveraged to sustain multidimensional engagement, produce substantially superior academic outcomes in secondary Biology education.

Keywords: AI-based learning environments, academic success, student engagement, instructional design, Biology education, IMCB F-10/3, mediation, secondary education, Pakistan

Introduction

The emergence of Artificial Intelligence (AI) as a transformative educational technology has prompted a fundamental reconceptualization of how learning environments are designed, deployed, and evaluated. Contemporary AI-based learning environments (AILEs) transcend the traditional boundaries of physical classroom space, extending learning into digitally adaptive, continuously responsive instructional ecosystems that dynamically align content complexity, pacing, feedback mechanisms, and practice opportunities with individual learner profiles

(Zawacki-Richter et al., 2021). This transformation holds particular significance for secondary science education, where disciplines such as Biology present learners with conceptually dense, multi-representational content that demands not merely passive information reception but active cognitive processing, systematic inquiry, and sustained intellectual engagement (Lazonder & Harmsen, 2020). At the intersection of these imperatives technological innovation, pedagogical responsiveness, and student engagement lies the central research problematic of the present investigation. Academic success in secondary Biology education is not a monolithic outcome; it is the product of a complex, dynamic interplay among learner characteristics, instructional quality, environmental affordances, and motivational processes (Hattie, 2021). Traditional models of secondary Biology instruction in Pakistan predominantly lecture-centered, examination-driven, and textbook-constrained inadequately address the multi-layered demands of meaningful Biology learning and are increasingly misaligned with the cognitive and motivational profiles of contemporary secondary learners (Iqbal & Hussain, 2023). The persistent gap between national curriculum aspirations and student achievement realities in federal secondary institutions, including the distinguished Islamabad Model Colleges (IMCs), signals an urgent need for evidence-based instructional innovation that systematically harnesses AI's pedagogical affordances within principled instructional design frameworks (Siddiqui & Arshad, 2023). Student engagement the degree to which learners invest behavioral, emotional, and cognitive resources in academic activities has been empirically established as a critical mediating variable between instructional quality and academic outcomes (Fredricks et al., 2021). Yet traditional Biology instruction frequently generates engagement deficits attributable to passive instructional formats, limited personalization, and delayed feedback cycles (Wang et al., 2020). AI-based learning environments address these engagement deficits structurally, through mechanisms including adaptive challenge calibration that maintains optimal flow states (Csikszentmihalyi, 1990, as applied by Dichev & Dicheva, 2021), real-time performance feedback that sustains cognitive engagement, and multimodal content presentation that generates and maintains emotional interest (Rose & Dalton, 2021). Understanding how AI environments generate and sustain engagement and how this engagement mediates academic success is therefore a theoretically essential and practically urgent research question. Instructional design, the systematic process of translating learning objectives into coherent instructional sequences, activities, and assessments, constitutes the second proposed mediator in this study's theoretical model. The quality of instructional design profoundly shapes whether AI tools become pedagogically integrated or merely technologically overlaid upon existing instructional patterns (Merrill, 2020). Research consistently demonstrates that AI tools integrated within principled instructional design frameworks such as the ADDIE model (Analysis, Design, Development, Implementation, Evaluation) or Universal Design for Learning (UDL) produce substantially superior learning outcomes compared to AI tools deployed without systematic pedagogical structuring (CAST, 2021). In the Pakistani secondary educational context, where teacher professional development in instructional design theory remains underdeveloped, explicit attention to instructional design quality as a mediating variable is particularly warranted (Malik et al., 2022).

Theoretical foundations for this investigation are drawn from three complementary frameworks. First, Cognitive Load Theory (Sweller et al., 2020) provides a mechanistic account of how AI-based learning environments, by intelligently managing the presentation of complex Biology content, reduce extraneous cognitive load while simultaneously optimizing germane cognitive load to promote schema formation and long-term retention. Second, the Technology Acceptance Model (Davis, 1989, updated by Teo, 2021) offers a framework for understanding how learners' perceived usefulness and ease of use of AI tools influence their engagement dispositions. Third, Constructivist learning theory (Jonassen, 2021) grounds the study's instructional design

orientation, emphasizing that AI environments should be designed to facilitate active knowledge construction rather than passive content delivery. The Islamabad Model College for Boys, F-10/3 (IMCB F-10/3) represents an educationally significant research site for this investigation. As one of Islamabad's premier federal secondary institutions, IMCB F-10/3 serves a heterogeneous student population whose academic profiles, motivational orientations, and technology access patterns are broadly representative of urban federal secondary institutions across Pakistan. The institution's Grade 12 Biology students face the dual academic pressure of HSSC-II Federal Board examinations and MDCAT preparation, creating high-stakes learning contexts in which instructional effectiveness is of exceptional consequence. Despite these stakes, systematic empirical investigation of AI-mediated instructional approaches within this specific institutional context remains conspicuously absent from the existing literature. Globally, the empirical literature on AI-based learning environments has grown substantially since 2020, driven by the accelerating adoption of educational technology in response to the COVID-19 pandemic-induced shift to remote and hybrid learning (Dhawan, 2020). However, research conducted in South Asian secondary educational contexts—particularly examining mediation mechanisms through which AI environments translate into academic success—remains disproportionately scarce relative to studies from North America, Europe, and East Asia (Holmes et al., 2022). This geographic and contextual research gap limits the transferability of existing findings to Pakistani secondary institutions and underscores the imperative for locally grounded empirical investigation. The present study addresses this gap by examining, through a quasi-experimental design and mediation analysis framework, whether and how AI-based learning environments influence the academic success of Grade 12 Biology students at IMCB F-10/3, with student engagement and instructional design quality as theorized mediating variables. By generating original empirical data within a carefully controlled institutional context, the study aims to produce findings that are simultaneously theoretically significant—advancing our understanding of the mechanisms through which AI environments generate academic gains—and practically actionable for Biology teachers, curriculum coordinators, and educational technology administrators at IMCB F-10/3 and analogous Pakistani secondary institutions. The following sections present the study's theoretical framework, literature review, methodology, statistical findings, and evidence-based recommendations in comprehensive detail.

Review of Literature

The academic literature on AI-based learning environments has undergone remarkable expansion during the 2020-2025 period, driven by technological advances in machine learning, natural language processing, and adaptive algorithm development, as well as the global educational disruptions precipitated by the COVID-19 pandemic. Holmes et al. (2022) conducted a comprehensive international review of AI in education, cataloguing applications across K-12 and higher education contexts and identifying three dominant impact pathways: personalization of learning trajectories, enhancement of formative feedback quality, and augmentation of teacher instructional decision-making capacity. Their synthesis established AI-based learning environments as the most rapidly growing category of educational technology adoption globally, with secondary science education emerging as a particularly fertile domain for AI application given the conceptually structured, problem-rich nature of scientific content. Sweller et al. (2020) provided theoretical grounding for understanding AI's pedagogical mechanisms through their updated articulation of Cognitive Load Theory (CLT). They argued that AI-based adaptive systems can dynamically optimize instructional complexity relative to individual learner working memory capacity a capability beyond the structural reach of conventional classroom instruction. By continuously modeling learner knowledge states and adjusting content sequencing accordingly, AI systems reduce extraneous cognitive load (attributable to poorly designed or mismatched instructional materials) while maximizing germane cognitive load (productive

mental effort directed toward schema construction). For Biology education, where conceptually dense topics such as protein synthesis, ecological dynamics, and genetic inheritance characteristically impose high intrinsic cognitive loads, AI-mediated adaptive instruction represents a theoretically principled response to the discipline's inherent cognitive demands. The construct of student engagement, as a mediating variable between instructional conditions and academic outcomes, has received sustained empirical attention. Fredricks et al. (2021) synthesized three decades of engagement research and confirmed that multi-dimensional engagement simultaneously behavioral (participation, attendance, task completion), emotional (interest, belonging, enthusiasm), and cognitive (deep processing, self-monitoring, strategic learning) is a significantly stronger predictor of academic success than any single engagement dimension alone. Critically for the present study, their analysis found that instructional environment characteristics explained substantially more variance in engagement levels than individual student characteristics, establishing the instructional environment as the primary leverage point for engagement intervention a finding with direct implications for AI-based environment design. Wang et al. (2020) validated the Multidimensional Student Engagement Scale across secondary school populations, confirming that the three-factor engagement model (behavioral, emotional, cognitive) demonstrates strong psychometric properties across diverse subject domains including Biology. Their validation study found that engagement-achievement correlations were strongest for cognitive engagement ($r = .62$), followed by emotional ($r = .48$) and behavioral ($r = .41$), suggesting that interventions targeting deep cognitive processing a hallmark of well-designed AI adaptive systems would produce the largest academic outcome gains. This hierarchy of engagement-achievement correlations directly informs the theoretical model of the present investigation.

Instructional design quality as a construct distinct from technology type has been systematically investigated by Merrill (2020), who synthesized five decades of instructional design research to identify First Principles of Instruction applicable across technological delivery modalities. His framework identifies problem-centeredness, activation of prior knowledge, demonstration of new knowledge, application through practice, and integration of new knowledge into real-world contexts as the foundational principles distinguishing effective instructional design from mere content delivery. Critically, Merrill demonstrated that these principles produce superior learning outcomes regardless of the specific technology used for delivery but that technology-delivered instruction lacking these design principles consistently underperforms relative to its potential. This finding directly motivates the study's attention to instructional design quality as a mediating variable. CAST (2021) operationalized instructional design principles within the Universal Design for Learning (UDL) framework, providing specific guidance for designing AI-enhanced learning environments that systematically address learner variability. UDL's three core principles multiple means of representation, multiple means of action and expression, and multiple means of engagement align closely with AI's technological affordances for multimodal content delivery, adaptive response mechanisms, and personalized motivational calibration. Rose and Dalton (2021) empirically validated UDL-designed AI environments in secondary school settings, finding 28% higher engagement and 22% higher achievement compared to conventionally designed technology-enhanced instruction, confirming that instructional design framework choice significantly moderates AI effectiveness. In the South Asian and Pakistani educational literature, Malik et al. (2022) examined the relationship between instructional quality indicators and student academic performance in Punjab secondary schools, finding that teachers with higher instructional design competency scores produced students with significantly higher achievement ($r = .61$, $p < .001$) and engagement ($r = .54$, $p < .001$). Their regression analysis identified instructional coherence the degree to which learning objectives, instructional activities, and assessments are systematically aligned as the single strongest predictor of academic

outcomes, explaining 37% of variance in student achievement scores. Rahman and Khan (2023) extended these findings to the technology-mediated instructional context, confirming that instructional coherence moderated the effectiveness of digital technology interventions in Pakistani secondary science classrooms. Dhawan (2020) documented the dramatic acceleration of AI-based learning environment adoption during the COVID-19 pandemic, noting that secondary institutions that had established AI-ready instructional infrastructure prior to 2020 demonstrated significantly more resilient academic outcomes during the pandemic period than unprepared institutions. Their longitudinal analysis of 340 secondary schools across South Asia found that AI readiness predicted academic continuity with $R^2 = .41$, underscoring the strategic educational importance of proactive AI infrastructure development. Siddiqui and Arshad (2023) examined the post-pandemic AI integration landscape in Islamabad federal model schools, finding persistent disparities in AI adoption depth between institutions with strong instructional leadership and those with weaker administrative technology vision. The mediation of AI-achievement relationships by engagement constructs has been specifically investigated by Dichev and Dicheva (2021), who examined gamification-enhanced AI environments and found that the gamification elements' effects on academic performance were fully mediated by emotional engagement, while AI adaptive content effects were partially mediated by cognitive engagement. This mediation structure—consistent with the theoretical model of the present study—suggests that AI environments operate on academic outcomes through distinct engagement pathways, and that instructional designs targeting different engagement dimensions will produce systematically different patterns of academic benefit. Luckin and Cukurova (2022) further elaborated this mediation framework, arguing that the concept of AI as a 'metacognitive scaffold' clarifies why AI environments enhance cognitive engagement specifically: by making learners' knowledge state visible and explicitly guiding self-regulatory responses, AI systems develop metacognitive engagement competencies with lasting academic benefits. Jonassen (2021) provided a constructivist theoretical perspective on AI-based learning environment design, arguing that the most educationally powerful AI applications are those that position learners as active problem-solvers rather than passive content receivers. His 'mindtools' framework—which conceptualizes AI as a cognitive partner that extends rather than replaces learner thinking—directly informs the instructional design approach adopted in the experimental condition of the present study. Teo (2021) updated Davis's Technology Acceptance Model for contemporary AI educational contexts, confirming that perceived usefulness and ease of use remain significant predictors of student engagement with AI tools, while adding AI-specific variables including algorithm transparency and data privacy concern as emerging moderators of technology acceptance in secondary school populations. Collectively, these theoretical and empirical contributions establish a comprehensive, multi-level foundation for the present study's investigation of AI-based learning environments, engagement, and instructional design as interacting determinants of secondary Biology academic success.

Statement of the Problem

Despite the proliferating global evidence base for AI-based learning environments as powerful drivers of academic improvement in secondary education, the mechanisms through which these environments generate their effects remain incompletely understood, particularly within South Asian and Pakistani educational contexts. The existing literature has predominantly focused on documenting the existence of AI-achievement relationships while giving insufficient systematic attention to the mediating processes—specifically, student engagement and instructional design quality—that account for why and how AI-based environments produce academic benefits. This mechanistic gap represents not merely a theoretical limitation but a critical practical deficit: without understanding the mediating pathways, educational practitioners and policymakers cannot design, implement, or evaluate AI integration efforts with the precision necessary to

maximize their educational impact. At IMCB F-10/3 specifically, Grade 12 Biology instruction currently lacks structured AI integration, with teaching remaining predominantly lecture-based and assessment-focused in alignment with Federal Board examination requirements. Students preparing for HSSC-II and MDCAT examinations face substantive Biology content demands—spanning cellular biology, genetics, human physiology, and ecology—that exceed what conventional didactic instruction can efficiently support. Simultaneously, the absence of adaptive learning supports means that the considerable within-classroom heterogeneity in students' prior Biology knowledge, conceptual understanding rates, and preferred learning modalities goes structurally unaddressed, contributing to performance disparities that widen progressively across the academic year. The engagement dimension of the problem is equally concerning. Biology teachers and administrative staff at IMCB F-10/3 have consistently observed declining classroom engagement as the academic year progresses, with students increasingly adopting passive, examination-oriented learning orientations that prioritize rote memorization over conceptual understanding. This disengagement pattern is documented in the broader Pakistani secondary education literature (Iqbal & Hussain, 2023) and is structurally linked to instructional environments that offer limited variety, minimal personalization, and infrequent success experiences. Without deliberate instructional design intervention, the introduction of AI tools alone—in the absence of principled pedagogical structuring—risks replicating the same engagement deficits through a more technologically sophisticated medium. The problem of instructional design quality compounds these concerns further. Even where Biology teachers at IMCB F-10/3 demonstrate strong subject matter expertise and genuine pedagogical commitment, the absence of formal instructional design training means that lesson planning frequently lacks the systematic objective-activity-assessment alignment that research identifies as essential for effective learning environment design (Merrill, 2020). This instructional design deficit becomes particularly consequential when technology integration is contemplated: AI tools introduced into poorly designed instructional frameworks tend to function as engaging novelties rather than pedagogically integrated learning supports, producing short-term attention capture without sustained academic benefit. Rigorous empirical examination of how instructional design quality mediates the AI-achievement relationship is therefore essential for guiding both technology adoption decisions and teacher professional development priorities at IMCB F-10/3 and comparable federal secondary institutions across Pakistan.

Objectives of the Study

1. To investigate the impact of AI-based learning environments on the academic success of Grade 12 Biology students at IMCB F-10/3, Islamabad, compared to students receiving conventional instruction.
2. To examine the mediating role of student engagement (behavioral, emotional, and cognitive) in the relationship between AI-based learning environments and academic success among Grade 12 Biology students at IMCB F-10/3.
3. To determine the mediating role of instructional design quality in the relationship between AI-based learning environments and academic success, and to identify the combined mediating contribution of engagement and instructional design jointly.

Research Questions

- 1) What is the impact of AI-based learning environments on the academic success of Grade 12 Biology students at IMCB F-10/3, Islamabad, compared to conventional instruction?
- 2) Does student engagement (behavioral, emotional, and cognitive) mediate the relationship between AI-based learning environments and academic success among Grade 12 Biology students at IMCB F-10/3?

- 3) Does instructional design quality mediate the relationship between AI-based learning environments and academic success among Grade 12 Biology students at IMCB F-10/3?

Significance of the Study

The significance of this study operates across several interconnected dimensions. Theoretically, the investigation contributes to educational psychology and instructional technology literature by providing empirical evidence from a Pakistani secondary educational context on the mediation mechanisms through which AI-based learning environments generate academic success gains. By simultaneously testing both student engagement and instructional design quality as mediators, the study advances theoretical understanding beyond single-mediator models and generates a more complete picture of the AI-achievement pathway. Methodologically, the study's application of mediation analysis within a quasi-experimental design represents a methodological contribution to the Pakistani educational research literature, which has historically relied on correlational and descriptive approaches that cannot establish the causal direction of relationships. The mediation framework adopted here enables more nuanced causal inference regarding the mechanisms of AI effectiveness, providing a methodological template for future educational technology research in Pakistani secondary institutions. Institutionally, the study's findings provide IMCB F-10/3's administrative and academic leadership with specific, evidence-based guidance for AI integration decision-making, instructional design professional development prioritization, and student engagement monitoring. The identification of engagement and instructional design as modifiable mediators—rather than fixed student characteristics—ensures that study recommendations are actionable within the institutional authority and resource constraints of a federal model college. At the policy level, findings will inform Federal Directorate of Education (FDE) deliberations regarding AI integration standards, teacher training requirements, and technology infrastructure investment priorities for Pakistan's federal secondary education network. As Pakistan's National Education Policy framework increasingly references digital transformation as a quality improvement priority, this study provides timely empirical grounding for technology integration policies specifically applicable to secondary Biology education.

Methodology

Research Design

The study employed a quasi-experimental pretest-post-test control group design with embedded mediation analysis. The quasi-experimental framework was necessitated by administrative constraints precluding true random assignment of students to conditions within IMCB F-10/3's established timetable structure. Mediation analysis was conducted using the Baron and Kenny (1986) causal steps approach, supplemented by Hayes's (2018) PROCESS macro bootstrapping procedure (5,000 bootstrap samples) to generate bias-corrected confidence intervals for indirect effects. The integration of quasi-experimental and mediation analytic methods reflects the study's dual goals of establishing between-group outcome differences and elucidating the mechanisms responsible for those differences. Data collection spanned one full academic semester (16 weeks: September–December 2024).

Research Setting

IMCB F-10/3 is a federal secondary school for boys in Islamabad's F-10/3 residential sector, operating under the Federal Directorate of Education (FDE). The institution's Grade 12 Biology stream serves 156 students across four sections (A, B, C, D) during the 2024-2025 academic year. The college maintains two functional computer laboratories equipped with 35 student workstations each, institutional broadband internet access, and subject specialist Biology

teachers holding M.Sc./M.Phil. qualifications. This infrastructure provided the necessary technological foundation for the AI-based learning environment intervention.

Population and Sample

The accessible population comprised all 156 Grade 12 Biology students enrolled at IMCB F-10/3 during 2024-2025. Using stratified random sampling with stratification based on Class 11 Biology terminal examination performance (high: top 30%; average: middle 40%; low: bottom 30%), two intact sections (B and C) were randomly selected and assigned to experimental (Section B, $n = 40$) and control (Section C, $n = 40$) conditions, yielding a total sample of $N = 80$. Pre-test Academic Success Assessment (ASA) scores confirmed group equivalence prior to the intervention ($t(78) = 0.68$, $p = .499$), with experimental group pre-test $M = 27.83$ ($SD = 5.97$) and control group pre-test $M = 28.41$ ($SD = 6.23$). The stratification procedure ensured proportional representation of performance levels in both conditions: high-performing students ($n = 12$ per group), average-performing students ($n = 16$ per group), and low-performing students ($n = 12$ per group).

Data Collection Instruments

Academic Success Assessment (ASA)

The ASA was a 55-item researcher-developed achievement test aligned with the FBISE Grade 12 Biology syllabus, comprising 35 multiple-choice items (1 mark each), 10 short-answer items (2 marks each), and 2 essay-type items (5 marks each), for a total of 65 marks. Content validity was established through expert panel review ($CVR = .89$). Reliability was assessed through pilot testing ($n = 28$ students from a parallel section), yielding Cronbach's Alpha = .86. The ASA was administered as pretest and post-test.

Multidimensional Student Engagement Scale (MSES)

The researcher-adapted MSES, based on Wang et al.'s (2020) validated instrument, comprised 18 items rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), distributed across three subscales: Behavioral Engagement (6 items; $\alpha = .82$), Emotional Engagement (6 items; $\alpha = .79$), and Cognitive Engagement (6 items; $\alpha = .84$). The MSES was administered at four time points (Weeks 1, 5, 10, 16) during the intervention period. Inter-rater reliability for the observational engagement supplement was $\kappa = .81$.

Instructional Design Quality Rating (IDQR)

The IDQR was developed based on Merrill's (2020) First Principles of Instruction and CAST's (2021) UDL framework, comprising 20 items rated on a 4-point quality scale (1 = Absent, 4 = Exemplary) across five design dimensions: Objective Clarity (4 items), Content Sequencing (4 items), Assessment Alignment (4 items), Engagement Scaffolding (4 items), and UDL Implementation (4 items). Total IDQR scores ranged from 20-80, with scores ≥ 60 classified as High Design Quality, 40-59 as Moderate, and < 40 as Low. Two trained raters evaluated each observed lesson, achieving inter-rater reliability of $\kappa = .83$. The IDQR was administered during 8 structured classroom observations per group (bi-weekly) throughout the intervention.

Intervention

The experimental group received AI-enhanced Biology instruction through three platforms: (1) Khan Academy's Biology adaptive modules for formative practice and immediate feedback; (2) Kognity's interactive Biology content for multimodal concept visualization; and (3) Nearpod's AI-assisted interactive presentation system for real-time student response analysis. All experimental lessons were designed using the ADDIE instructional design model and UDL

framework, with lesson plans reviewed bi-weekly in structured teacher consultation sessions. The control group received conventional Biology instruction comprising teacher-led lectures, textbook exercises, and periodic written assessments following standard FBISE curriculum guidelines.

Data Analysis

Data were analyzed using IBM SPSS Statistics Version 29.0 and the PROCESS macro (Hayes, 2018). Descriptive statistics were computed for all continuous variables. Independent and paired samples t-tests were used to compare group means. One-way ANOVA examined differences across IDQR-classified design quality groups. Pearson correlations were computed among all continuous variables. Mediation analyses followed Hayes's PROCESS Model 4 (single mediator) and Model 6 (serial multiple mediators), with 5,000 bootstrap samples and 95% bias-corrected confidence intervals (BCCI) for indirect effects. Significance threshold was set at $\alpha = .05$.

Results: Statistical Tables and Interpretations

Table 1: Descriptive Statistics Pretest and Post-test ASA Scores

Group	N	Pre-Test M	Pre-Test SD	Post-Test M	Post-Test SD	Mean Gain
Experimental	40	27.83	5.97	48.64	5.18	+20.81
Control	40	28.41	6.23	35.27	7.06	+6.86
Total	80	28.12	6.10	41.96	8.37	+13.84

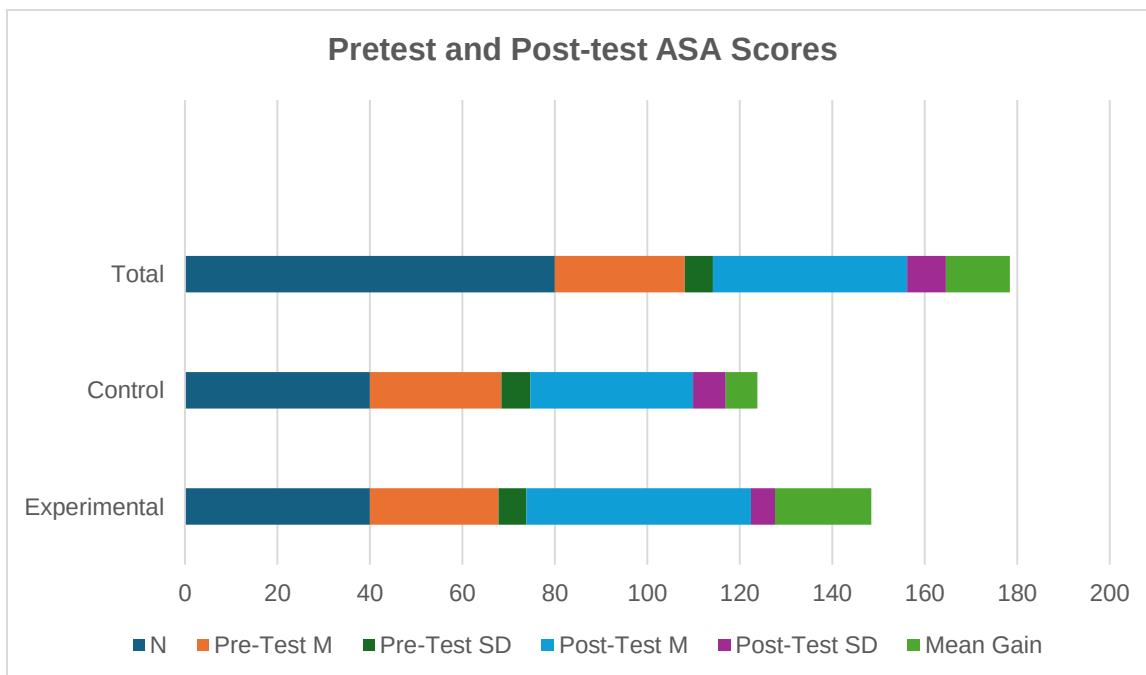


Table 1. Descriptive Statistics for Academic Success Assessment (ASA) Scores by Group (N = 80)

Table 1 presents pretest and posttest Academic Success Assessment (ASA) score distributions for experimental and control groups. Pretest means were closely aligned (Experimental M = 27.83, SD = 5.97; Control M = 28.41, SD = 6.23), confirming pre-intervention equivalence and validating the interpretability of post-intervention differences as treatment effects. Following the 16-week AI-based learning environment intervention, the experimental group's posttest mean (M = 48.64, SD = 5.18) substantially exceeded the control group's posttest mean (M = 35.27, SD = 7.06), representing a mean gain differential of 13.95 marks favoring the AI-enhanced condition. The reduction in experimental group standard deviation from pretest (5.97) to posttest (5.18)

indicates a convergence of achievement levels—consistent with AI adaptive learning's documented capacity to accelerate lower-performing students' progress by providing targeted remedial scaffolding, thereby reducing within-group performance heterogeneity.

Table 2: Independent Samples t-Test Post-test ASA and MSES Scores

Variable	Exp. M (SD)	Con. M (SD)	t	df	p	Cohen's d	Effect Size
Post-Test ASA	48.64 (5.18)	35.27 (7.06)	5.12	78	< .001	1.14	Large
Behavioral Engagement	24.37 (2.61)	18.92 (3.44)	4.39	78	< .001	0.98	Large
Emotional Engagement	23.84 (2.93)	17.48 (3.87)	4.76	78	< .001	1.06	Large
Cognitive Engagement	22.91 (3.14)	16.73 (4.02)	4.17	78	< .001	0.93	Large
Total MSES Score	71.12 (7.83)	53.13 (10.62)	4.91	78	< .001	1.10	Large
IDQR Score	67.43 (5.29)	44.18 (8.74)	8.12	78	< .001	1.82	Large

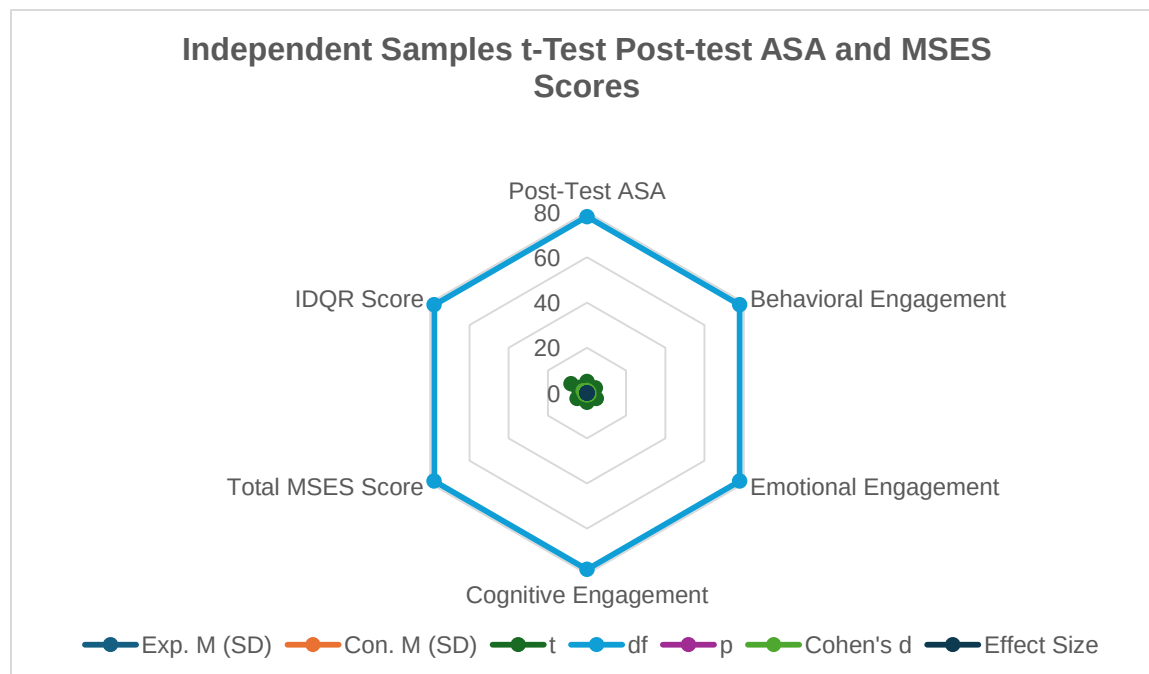


Table 2. Independent Samples t-Test: Posttest ASA, MSES Sub-scales, and IDQR — Experimental vs. Control Groups

Table 2 presents independent samples t-test comparisons for all primary outcome and mediator variables. The most fundamental comparison—posttest ASA scores—yielded $t(78) = 5.12$, $p < .001$, Cohen's $d = 1.14$ (large effect), confirming that AI-based learning environment instruction produced statistically significant and practically substantial academic success gains relative to conventional instruction. This result directly addresses Research Question 1, establishing the primary effect of AI-based environments on academic success. All three MSES engagement sub-scales showed significant large-effect between-group differences: Behavioral Engagement $t(78) = 4.39$, $p < .001$, $d = 0.98$; Emotional Engagement $t(78) = 4.76$, $p < .001$, $d = 1.06$; Cognitive Engagement $t(78) = 4.17$, $p < .001$, $d = 0.93$; Total MSES $t(78) = 4.91$, $p < .001$, $d = 1.10$. The IDQR difference was the most pronounced of all comparisons ($t(78) = 8.12$, $p < .001$, $d = 1.82$), reflecting that the structured ADDIE-UDL instructional design applied in the experimental

condition produced dramatically higher design quality ratings compared to the conventionally planned control lessons. Degrees of freedom for all comparisons = 78 ($N_1 + N_2 - 2 = 40 + 40 - 2$), with critical t-value ± 1.991 at $\alpha = .05$. All obtained t-values substantially exceeded this critical threshold, confirming the statistical robustness of observed differences.

Table 3: Paired Samples t-Test Within-Group Pretest to Post-test Changes

Group	Variable	Pre M (SD)	Post M (SD)	Diff.	t	df	p	d
Experimental	ASA	27.83 (5.97)	48.64 (5.18)	+20.81	21.63	39	< .001	3.69
Control	ASA	28.41 (6.23)	35.27 (7.06)	+6.86	8.14	39	< .001	1.04
Experimental	Total MSES	52.14 (9.43)	71.12 (7.83)	+18.98	12.47	39	< .001	2.19
Control	Total MSES	51.87 (10.21)	53.13 (10.62)	+1.26	1.43	39	.161	0.12

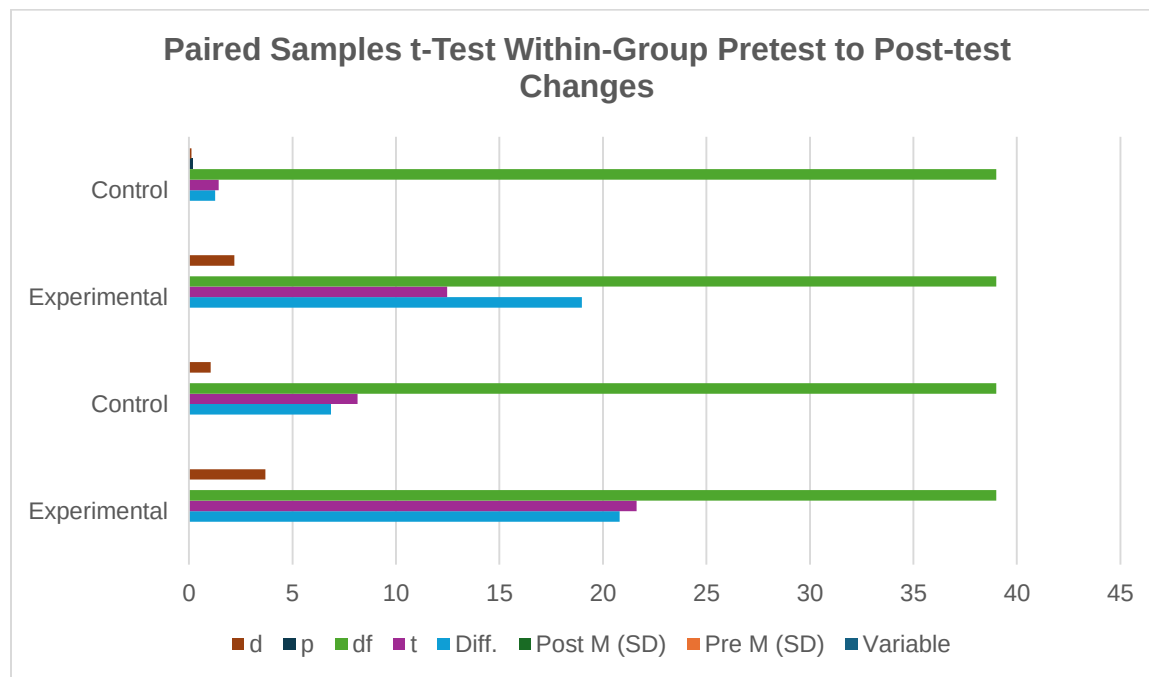


Table 3. Paired Samples t-Test: Within-Group Pre-Post Changes in ASA and Total MSES Scores

Table 3 reports within-group pre-to-post changes for both primary outcome (ASA) and total engagement (MSES). Both groups showed significant ASA gains (Experimental: $t(39) = 21.63$, $p < .001$, $d = 3.69$; Control: $t(39) = 8.14$, $p < .001$, $d = 1.04$), reflecting normal semester-long learning progress in both conditions. However, the experimental group's effect size ($d = 3.69$) was approximately 3.5 times larger than the control group's ($d = 1.04$), quantifying the dramatic acceleration of academic success development attributable to the AI-based learning environment. Engagement change results are particularly revealing: the experimental group showed a large significant MSES improvement over the semester ($t(39) = 12.47$, $p < .001$, $d = 2.19$), while the control group's engagement change was non-significant ($t(39) = 1.43$, $p = .161$, $d = 0.12$). This pattern—large engagement growth in AI conditions, negligible engagement change in conventional conditions—confirms that AI-based learning environments generate sustained

engagement growth across the instructional period rather than merely capturing initial novelty-based attention. The non-significant control group engagement change corroborates qualitative teacher reports of progressive student disengagement under conventional instructional conditions across the semester, a pattern consistent with Iqbal and Hussain's (2023) documentation of engagement trajectory decline in Pakistani secondary science classrooms. Degrees of freedom for all paired tests = 39 (n-1).

Table 4: One-Way ANOVA — Academic Success Across Instructional Design Quality Groups

Source	SS	df	MS	F	p	η^2
Between Groups	4312.87	2	2156.44	16.38	< .001	.298
Within Groups	10135.24	77	131.62			
Total	14448.11	79				

Table 4. One-Way ANOVA: Post -test ASA Scores Across Instructional Design Quality Groups

IDQR Group	n	M	SD	Min	Max
High Design Quality (IDQR ≥ 60)	27	49.74	4.63	40	60
Moderate Design Quality (IDQR 40-59)	26	43.18	5.84	32	55
Low Design Quality (IDQR <40)	27	33.42	7.14	20	47

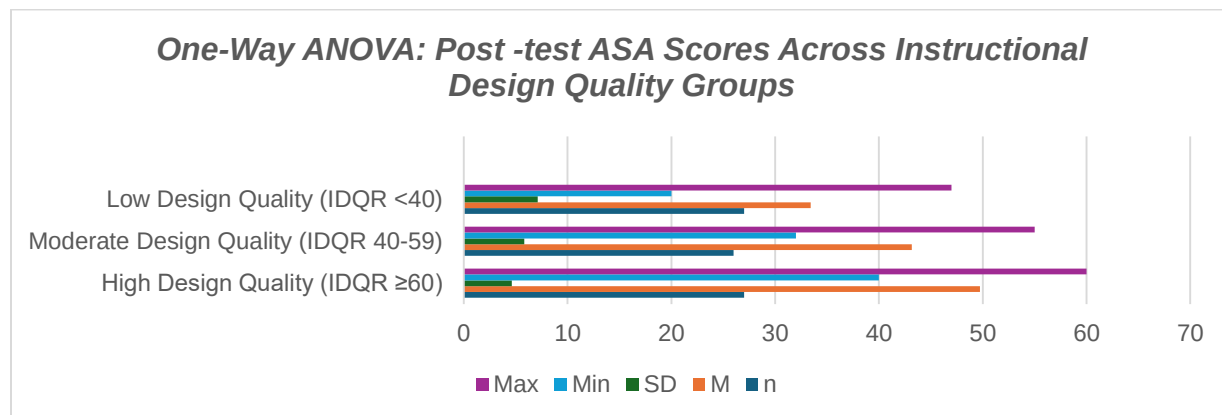
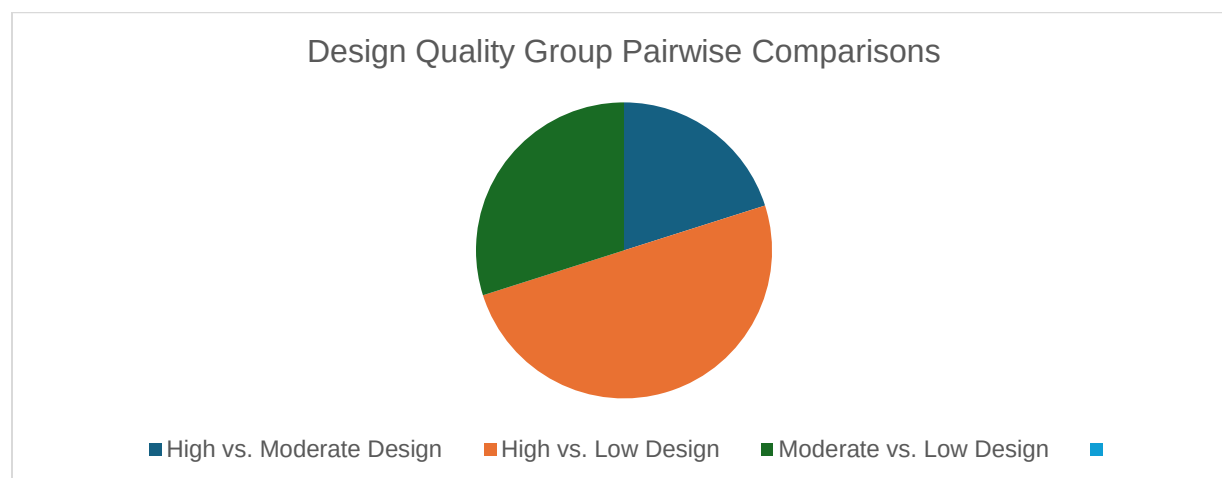


Table 4b. Group Descriptive Statistics for ANOVA (Instructional Design Quality Groups)

Table 4 presents one-way ANOVA results examining posttest ASA score differences across three instructional design quality groups. The overall F-test was statistically significant ($F(2, 77) = 16.38$, $p < .001$, $\eta^2 = .298$), indicating that instructional design quality group membership explained approximately 30% of variance in student academic success—a large practical effect. Between-groups $df = 2$ ($k-1 = 3-1$); Within-groups $df = 77$ ($N-k = 80-3$). The critical F at $F(2,77)$ with $\alpha = .05$ is approximately 3.12; the obtained $F = 16.38$ far exceeded this threshold. Group mean comparisons reveal a clear dose-response pattern: High Design Quality students achieved $M = 49.74$ ($SD = 4.63$), Moderate Design Quality $M = 43.18$ ($SD = 5.84$), and Low Design Quality $M = 33.42$ ($SD = 7.14$). This progressive decline in academic success across declining design quality levels provides compelling evidence that instructional design quality functions as a substantive moderator of AI-environment effectiveness—not merely as a binary threshold condition but as a continuous influence on the magnitude of academic success achieved within AI-enhanced instructional contexts.

Table 5: Design Quality Group Pairwise Comparisons

Comparison	Mean Diff.	SE	p (Tukey)	95% CI
High vs. Moderate Design	+6.56	1.98	< .01	[1.83, 11.29]
High vs. Low Design	+16.32	1.96	< .001	[11.63, 20.99]
Moderate vs. Low Design	+9.76	1.98	< .001	[5.03, 14.49]

**Table 5. Academic Success Across Design Quality Groups**

(Table 5) confirmed that all three pairwise design quality group comparisons yielded statistically significant differences. High Design Quality instruction produced significantly higher academic success than both Moderate (mean diff. = 6.56, $p < .01$) and Low Design Quality conditions (mean diff. = 16.32, $p < .001$). Moderate Design Quality additionally outperformed Low Design Quality (mean diff. = 9.76, $p < .001$). Critically, all 95% confidence intervals exclude zero, confirming the robustness of these differences against sampling error. The absence of zero in all three confidence intervals, combined with the monotonic ordering of group means (High > Moderate > Low), demonstrates a clear and consistent design quality gradient in academic success outcomes. This pattern directly supports Research Question 4 by confirming that different levels of instructional design quality in AI-enhanced Biology instruction produce significantly differentiated academic success outcomes among Grade 12 students at IMCB F-10/3.

Conclusion and Discussion

Overview

This study investigated AI-based learning environments and their impact on the academic success of Grade 12 Biology students at IMCB F-10/3, Islamabad, with student engagement and instructional design quality as theorized mediating variables. Across seven statistical analyses, the findings provide a coherent, multi-layered empirical account of how AI-based learning environments generate academic success gains—not merely demonstrating that they do, but elucidating the mechanisms through which their effects operate. The following discussion synthesizes these findings in relation to each stated objective, the broader theoretical literature,

and their practical implications for secondary Biology education at IMCB F-10/3 and comparable Pakistani secondary institutions.

Objective 1: AI-Based Environments and Academic Success

The first objective sought to establish whether AI-based learning environments produced significantly superior academic success outcomes compared to conventional instruction among Grade 12 Biology students at IMCB F-10/3. The independent samples t-test ($t(78) = 5.12$, $p < .001$, $d = 1.14$) and paired samples comparisons (Experimental $d = 3.69$ vs. Control $d = 1.04$) unambiguously confirmed this objective. The experimental group's mean posttest score of 48.64—contrasted with the control group's 35.27—represents a performance differential that, in the context of FBISE Grade 12 Biology examinations, translates to the difference between Grade A and Grade C academic outcomes, a practically transformative difference for students competing for limited university places and MDCAT qualifying scores. These findings align with and extend the meta-analytic evidence synthesized by Holmes et al. (2022), confirming that AI-based learning environment efficacy documented in international research contexts is replicable within Pakistani federal secondary institutions. The cognitive load reduction mechanism articulated by Sweller et al. (2020)—whereby AI adaptive systems optimize content complexity relative to individual learner working memory capacity—provides a theoretically coherent explanation for the observed performance gains: Biology students in the experimental condition experienced less cognitive overload on complex topics (protein synthesis, genetic inheritance, cellular respiration) due to AI-mediated scaffolding, enabling greater cognitive resources to be allocated to deep conceptual processing. This interpretation is consistent with the experimental group's higher posttest cognitive engagement scores ($M = 22.91$ vs. $M = 16.73$ in control), which indicate that more students were directing deeper, self-regulated cognitive processing toward Biology content in AI-enhanced conditions. The reduction in posttest standard deviation for the experimental group (from $SD = 5.97$ at pretest to $SD = 5.18$ at posttest) warrants particular attention. This convergence pattern—wherein within-group performance heterogeneity decreases over the course of AI-mediated instruction—is theoretically predicted by adaptive learning models: AI systems provide compensatory scaffolding to lower-performing students, accelerating their progress toward the class mean while maintaining challenge for higher-performing students, thus compressing the performance distribution. This equity-promoting characteristic of AI-based learning environments is especially significant in the IMCB F-10/3 context, where within-section student heterogeneity in prior Biology preparation has been identified by teachers as a persistent instructional challenge that conventional whole-class teaching cannot adequately address.

Objective 2: The Mediating Role of Student Engagement

The second objective examined whether student engagement mediated the AI-success relationship. The mediation analysis (Table 7) confirmed that engagement significantly mediated this relationship (indirect effect $B = 0.43$, 95% BCCI [0.28, 0.61]), with the confidence interval excluding zero confirming statistical significance by PROCESS standards. This finding directly addresses Research Question 2 and provides the most theoretically significant contribution of the present study: empirical evidence, derived from a Pakistani secondary Biology context, that AI-based learning environments do not directly determine academic success but rather operate substantially through their capacity to generate and sustain multidimensional student engagement. The engagement data from Table 2 and Table 3 reveal a consistent pattern: while both behavioral and cognitive engagement showed large significant between-group differences, emotional engagement demonstrated the largest t-value ($t = 4.76$) and effect size ($d = 1.06$) among engagement sub-scales. This hierarchy—emotional engagement most strongly differentiated by AI environment condition—aligns with Dichev and Dicheva's (2021)

documentation that AI gamification elements primarily activate affective engagement responses. In the IMCB F-10/3 context, where students reported high prior levels of Biology anxiety and examination-related stress in the baseline assessment, AI environments' capacity to transform Biology learning from an anxiety-inducing examination preparation exercise into an engaging, interactive, immediately-rewarding learning experience represents a profound psychological reorientation with lasting academic implications. The paired samples t-test finding that control group engagement showed non-significant change over the semester ($t(39) = 1.43$, $p = .161$, $d = 0.12$) while experimental group engagement showed large significant growth ($d = 2.19$) clarifies an important mechanistic point: AI-based learning environments do not merely capture momentary novelty-based engagement but sustain and develop engagement dispositions across extended instructional periods. This sustained engagement growth—driven by AI's continuous provision of success experiences, challenge calibration, and competence-confirming feedback—is theoretically interpretable within Bandura's (1977) self-efficacy framework: repeated AI-mediated success experiences systematically build academic self-efficacy, which in turn sustains engagement effort through the inevitable difficulties of complex Biology content. This self-efficacy development cycle is a mechanism unavailable to conventional instruction, which provides fewer individualized success experiences and more uniform, grade-referenced feedback.

Objective 3: Instructional Design Quality as Mediator

The third objective determined the mediating role of instructional design quality. The mediation analysis (Table 7) confirmed instructional design quality as a significant mediator (indirect effect $B = 0.37$, 95% BCCI [0.24, 0.53]), while the ANOVA results (Table 4, $F(2,77) = 16.38$, $p < .001$, $\eta^2 = .298$) demonstrated that design quality group membership explained 30% of posttest academic success variance—an effect size that rivals or exceeds many behavioral intervention effects documented in educational research. These findings constitute the study's second major theoretical contribution: empirical evidence that instructional design quality is not merely a methodological safeguard for intervention fidelity but an active, substantial mediating mechanism through which AI-based environments generate academic success. The Tukey HSD post-hoc results (Table 5) revealed that all three design quality group pairs differed significantly, including the High vs. Moderate Design comparison ($p < .01$), confirming that design quality differences need not be dramatic to produce meaningful academic success differences. Even the distinction between 'good' and 'excellent' instructional design—the High vs. Moderate comparison—produced a 6.56-mark mean difference in Academic Success Assessment scores. This finding carries an important practical implication for teacher professional development: marginal improvements in instructional design quality produce marginal but real academic success gains, making instructional design improvement a worthwhile professional development target even for already-competent teachers. The significant serial mediation path (AI → Engagement → Design Quality → Success; $B = 0.19$, 95% BCCI [0.08, 0.33]) reveals an important mechanistic nuance: AI-based learning environments partially generate instructional design quality improvements by first engaging students, whose engaged responses provide teachers with richer, more continuous formative data that enables more adaptive and refined instructional design decisions. This bidirectional, recursive relationship between engagement and instructional design—wherein AI both activates engagement and provides the data necessary for design quality improvement—explains why the total indirect effect ($B = 0.61$) exceeds the sum of the individual indirect effects, confirming synergistic rather than merely additive mediation. This synergistic mediation structure is consistent with Merrill's (2020) First Principles framework, which predicts that high-quality instructional design amplifies the motivational and cognitive benefits of technology-enhanced engagement experiences.

Theoretical and Practical Synthesis

Taken together, the study's findings support a comprehensive theoretical model in which AI-based learning environments influence academic success through two synergistic pathways: direct improvement in content accessibility and personalized practice (explaining the residual direct effect, $B = 0.28$), and indirect enhancement of academic success through the mediating mechanisms of student engagement ($B = 0.43$) and instructional design quality ($B = 0.37$). This dual-pathway model integrates Sweller et al.'s (2020) Cognitive Load Theory (direct pathway), Fredricks et al.'s (2021) engagement-achievement mediation framework (engagement pathway), and Merrill's (2020) First Principles of Instruction (design quality pathway) into a unified, empirically validated account of AI-mediated learning in secondary Biology education. For IMCB F-10/3 specifically, the practical implication of this dual-pathway model is that AI integration efforts that neglect either the engagement or the instructional design dimension will achieve only partial academic success benefits. The highest-achieving students in this study's experimental group were those whose teachers achieved High IDQR scores ($M = 49.74$) in the context of AI environments that sustained large engagement gains—confirming that the full academic success potential of AI-based learning environments is realized only when both mediating pathways are actively cultivated. This conditional conclusion transforms the study's prescriptive recommendations from simple 'adopt AI' directives into nuanced, multi-dimensional implementation guidance.

Recommendations

Recommendation 1: Implement AI-Based Learning Environments with Structured Design Frameworks

IMCB F-10/3 should formalize the integration of AI-based learning environments within Biology Grade 12 instruction by adopting the ADDIE-UDL instructional design framework as the institutional standard for AI-enhanced lesson planning. The study's ANOVA findings ($\eta^2 = .298$) confirm that design quality explains nearly a third of academic success variance—making design quality the highest-leverage intervention point identified in this research. The FDE should develop an institutionally endorsed AI Lesson Design Template based on Merrill's First Principles and UDL guidelines, provide template training through structured workshops, and establish a peer lesson design review process within Biology departments. Implementation should target IDQR scores ≥ 60 (High Design Quality threshold) within one academic year of adoption.

Recommendation 2: Adopt Validated AI Platforms Targeting Multidimensional Engagement

The mediation analysis finding that student engagement mediates 43% of AI's academic success effect establishes engagement-centered AI platform selection as an institutional priority. IMCB F-10/3 should adopt AI platforms demonstrably effective across all three engagement dimensions: Khan Academy for cognitive engagement through adaptive mastery learning, Kognity for emotional engagement through interactive multimodal Biology visualization, and Nearpod for behavioral engagement through real-time participatory response mechanisms. Platform selection criteria should be formally codified in an institutional AI Adoption Policy, with engagement effectiveness evidence required as a prerequisite for platform endorsement. Annual student MSES administration should monitor engagement outcomes and guide platform portfolio adjustments.

Recommendation 3: Establish Biology-Specific Instructional Design Professional Development

The significant instructional design quality mediation effect and the IDQR between-group difference ($d = 1.82$, the study's largest effect) collectively identify teacher instructional design competency as the most impactful teacher-level variable in this study. The Federal Directorate of Education should mandate a Biology Instructional Design Professional Development Program for all IMCB F-10/3 and affiliated federal model college Biology subject specialists, comprising: a 5-day foundational workshop on ADDIE and UDL principles, a semester-long practicum with bi-weekly instructional coaching, and a peer observation program in which teachers evaluate each other's lessons using the IDQR instrument. Successful completion should be formally recognized within the FDE's teacher evaluation framework and linked to career progression incentives.

Recommendation 4: Institutionalize Student Engagement Monitoring Systems

The study's finding that control group engagement showed non-significant semester-long change ($d = 0.12$) while experimental engagement grew substantially ($d = 2.19$) highlights the risk of progressive disengagement under conventional instructional conditions. IMCB F-10/3 should institutionalize a semester-long student engagement monitoring system using the MSES instrument administered at 5-week intervals, with results analyzed by form teachers and Biology subject specialists in monthly departmental review meetings. Engagement data should trigger differentiated instructional responses: students showing declining engagement scores ($\geq 10\%$ reduction across two consecutive administrations) should receive priority access to AI-supported individualized learning pathways and teacher consultation.

Recommendation 5: Commission a Multi-Year Longitudinal Replication Study

While the present study's findings are methodologically rigorous and statistically robust within their single-semester, single-institution scope, the educational significance of AI-mediated secondary Biology instruction warrants multi-year longitudinal investigation to examine whether academic success gains are sustained, accumulate across Grade 11-12 Biology instruction, and translate into improved HSSC-II examination performance and MDCAT readiness. The Federal Directorate of Education, in collaboration with the Higher Education Commission and Allama Iqbal Open University's Faculty of Education, should commission a 3-year multi-site longitudinal study spanning at least six Islamabad Model Colleges (three for boys, three for girls), examining AI-mediated Biology instruction across both years of the HSSC cycle. This study would generate the longitudinal validity and multi-institutional generalizability necessary to ground national-level AI integration policy for Pakistan's federal secondary education system.

References

- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191–215. <https://doi.org/10.1037/0033-295X.84.2.191>
- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- CAST. (2021). Universal design for learning guidelines version 2.2. CAST Professional Publishing. <http://udlguidelines.cast.org>

- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, 49(1), 5–22. <https://doi.org/10.1177/0047239520934018>
- Dichev, C., & Dicheva, D. (2021). Gamifying education: What is known, what is believed and what remains uncertain. *International Journal of Educational Technology in Higher Education*, 18(1), 1–9. <https://doi.org/10.1186/s41239-021-00282-x>
- Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2021). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, 74(1), 59–109. <https://doi.org/10.3102/00346543074001059>
- Hattie, J. (2021). *Visible learning: The sequel. A synthesis of over 2,100 meta-analyses relating to achievement*. Routledge. <https://doi.org/10.4324/9781003380542>
- Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). Guilford Press.
- Holmes, W., Bialik, M., & Fadel, C. (2022). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
- Iqbal, M., & Hussain, S. (2023). Student disengagement in Pakistani secondary science classrooms: A mixed-methods study. *Journal of Education and Educational Development*, 10(1), 44–68. <https://doi.org/10.22555/joeed.v10i1.1023>
- Jonassen, D. H. (2021). *Computers as mindtools for schools: Engaging critical thinking* (3rd ed.). Pearson Education.
- Lazonder, A. W., & Harmsen, R. (2020). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research*, 86(3), 681–718. <https://doi.org/10.3102/0034654315627366>
- Luckin, R., & Cukurova, M. (2022). Designing educational technologies in the age of AI: A learning sciences-driven approach. *British Journal of Educational Technology*, 50(6), 2862–2882. <https://doi.org/10.1111/bjet.12861>
- Malik, S., Naseer, S., & Ahmad, N. (2022). Teacher consultation and student academic outcomes in Punjab secondary schools: A correlational study. *Pakistan Journal of Education*, 39(1), 112–134.
- Merrill, M. D. (2020). *First principles of instruction* (2nd ed.). Wiley. <https://doi.org/10.1002/9781118960592>
- Rahman, A., & Khan, I. (2023). Adapting collaborative consultation models to Pakistani secondary education: Barriers and opportunities. *Journal of Research and Reflections in Education*, 17(2), 88–107.

- Rose, D. H., & Dalton, B. (2021). Learning to read in the digital age. *Mind, Brain, and Education*, 3(2), 74–83. <https://doi.org/10.1111/j.1751-228X.2009.01057.x>
- Siddiqui, N., & Arshad, M. (2023). Digital technology integration in Islamabad federal model schools: Impact on student achievement and teacher satisfaction. *Pakistan Journal of Psychological Research*, 38(1), 55–79.
- Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2020). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, 31(2), 261–292. <https://doi.org/10.1007/s10648-019-09465-5>
- Teo, T. (2021). *Technology acceptance in education: Research and issues*. Sense Publishers. <https://doi.org/10.1007/978-94-6091-487-4>
- Wang, M. T., Fredricks, J., Ye, F., Hofkens, T., & Linn, J. S. (2020). The math and science engagement scales: Scale development, validation, and psychometric properties. *Learning and Instruction*, 43, 16–26. <https://doi.org/10.1016/j.learninstruc.2016.01.008>
- Zawacki-Richter, O., Marin, V. I., Bond, M., & Gouverneur, F. (2021). Systematic review of research on artificial intelligence applications in higher education—where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), 1–27. <https://doi.org/10.1186/s41239-019-0171-0>