International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 30, No. 9, September, 2025, pp. 2461-2471
Journal homepage: http://iieta.org/journals/isi

AI-Enhanced Predictive Modelling of Virtual Laboratory Microlearning in Online Distance Education

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https://doi.org/10.18280/isi.300920

Received: 20 June 2025
Revised: 30 August 2025
Accepted: 14 September 2025
Available online: 30 September 2025

Keywords:
virtual laboratory, microlearning, artificial intelligence, predictive modelling, online and distance learning, academic achievement

ABSTRACT

This study examines the impact of an AI-enhanced, virtual-laboratory (VL)–integrated microlearning model on learners' motivation, engagement, and academic achievement in online and distance learning (ODL). In a four-week experiment, 126 undergraduates were randomly assigned to VL-assisted microlearning, traditional microlearning, or lecture-based instruction. Data comprised pretest–posttest scores, motivation and engagement questionnaires, and interaction logs. ANCOVA/MANOVA showed that the VL-assisted group outperformed the others on cognitive and practical assessments, with large effects (Cohen's d > 0.80) and higher normalized gains (N-gain ≈ 0.72), and reported stronger motivation and engagement across dimensions. Beyond these tests, AI-based analysis uncovered non-linear relationships. It identified key behavioral predictors—such as simulation attempts, behavioral engagement, self-efficacy, and time-on-task—that explained performance differences. Comparative AI models (Gradient Boosting, Random Forest, SVM) confirmed these results, with Gradient Boosting achieving the highest accuracy (0.91) under 10-fold cross-validation. Interaction-log features outweighed demographic variables in predictive power, revealing hidden behavioural patterns linked to learning success. These findings indicate that coupling virtual laboratories with AI-driven analytics can improve both cognitive and affective outcomes, offering a scalable, data-informed approach to enhance ODL quality.

1. INTRODUCTION

Online and Distance Learning (ODL) has become a central educational model in the digital era, offering flexible access across geographical and socio-economic boundaries. However, students in ODL programs often exhibit lower persistence and completion rates than their counterparts in traditional settings, with withdrawal rates 3-15 percentage points higher [1]. Challenges in sustaining motivation, engagement, and self-regulation—exacerbated during large-scale shifts such as the COVID-19 pandemic—are key contributing factors [2]. The absence of physical interaction and real-time feedback can foster isolation, reduce participation, and increase dropout rates [3].

Microlearning has emerged as an effective strategy in ODL, delivering concise modules for short daily sessions and aligning with Cognitive Load Theory by minimizing overload and enhancing retention [4]. When integrated into Learning Management Systems (LMS), it enables flexible access, immediate feedback, and continuous engagement [5]. Empirical evidence shows its benefits. For instance, interactive mobile-based microlearning significantly improved learning performance and enjoyment compared to text-based formats [6].

Virtual laboratories—computer-based simulations replicating real lab experiences—provide engaging alternatives to physical labs [7]. When integrated into microlearning, these approaches contribute to greater motivation, stronger engagement, and enhanced academic achievement [8]. Yet most existing research relies on traditional statistical techniques (e.g., t-tests, ANCOVA) that cannot fully model complex, non-linear relationships among pedagogical and behavioural factors.

Advances in Educational Data Mining (EDM) and Learning Analytics (LA) have enabled the rich analysis of LMS logs, assessments, and surveys for performance prediction and early risk detection [9, 10]. Artificial Intelligence (AI) extends these capabilities by processing multi-dimensional behavioural, motivational, and demographic data to uncover patterns beyond the reach of conventional methods. In Virtual Laboratory-based ODL, AI-driven models can integrate diverse data sources—such as simulation logs, engagement scores, and assessment results—to provide predictive insights and personalized feedback.

This study employs AI-enhanced predictive and comparative modelling to evaluate and compare student motivation, engagement, and academic success in virtual laboratory-based ODL, addressing a critical methodological gap and contributing to both educational technology research and practice.

2. LITERATURE REVIEW

2.1 Microlearning approaches in ODL

Microlearning delivers content in small, focused units—typically 5–15 minutes—allowing flexible, self-paced study in diverse settings [5]. Its effective implementation in ODL requires well-designed professional development in technology-enhanced learning within virtual university settings and typically makes use of multimedia resources to support multiple modes of learner engagement [11].

A key advantage is improved retention through cognitive load management and concise content design [4, 12]. Interactive activities with timely feedback further enhance intrinsic motivation, emotional engagement, and participation [13]. However, the condensed format may limit deep reflection and complex problem-solving; from a Cognitive Load Theory perspective, excessive segmentation can hinder schema development [14]. Scaffolding strategies such as guided reflection or problem-based tasks can help maintain engagement [15].

Reduced collaborative interaction in online contexts can lower social presence, affecting satisfaction and peer engagement [16]. Studies on microlearning-supported flipped classrooms show that structured group tasks, peer feedback, and discussion forums can significantly boost participation and sustained engagement [13].

Virtual laboratories complement microlearning by enabling experiential practice and addressing depth limitations through hands-on application [7, 8].

2.2 Virtual laboratories in ODL

Virtual laboratories (VLs) are computer-based environments that replicate the functions of physical labs, enabling learners to conduct experiments, manipulate variables, and observe outcomes in simulated settings [17, 18]. They address barriers such as limited access to equipped facilities and disruptions to in-person teaching, as seen during COVID-19, thereby expanding practical learning opportunities in ODL [19].

Pedagogically, VLs align with constructivist learning principles, engaging students through authentic tasks, participation, and interaction [20]. Experiential learning theory further supports their value, emphasizing cycles of experience, reflection, conceptualization, and experimentation [21]. By enabling simulated scientific inquiry, VLs foster conceptual understanding, investigative skills, and practical application in STEM fields [22].

Empirical evidence shows VLs can yield outcomes comparable to traditional labs. For instance, Post-test scores of chemistry students using VLs were higher than those of lecture-only groups, with no significant difference from physical lab cohorts [7]. The provision of instant feedback, adaptive support, and interactive elements contributes to deeper levels of cognitive engagement.

VLs also support Self-Determination Theory needs—autonomy, competence, and relatedness—by allowing learner control, self-paced study, and instant feedback [23]. Gamification and digital badges have been shown to increase intrinsic motivation and sustained use [24, 25].

Challenges include infrastructure limitations, reduced tactile skill development in some disciplines, and varying levels of instructor readiness [26-28].

2.3 Role of AI in microlearning and virtual laboratories

Recent advances in Artificial Intelligence (AI) have expanded the potential of microlearning and virtual laboratories by supporting individualized learning pathways, immediate feedback, and dynamically adjusted instruction. Machine learning techniques—such as supervised algorithms and deep learning—can process multi-source educational data, including LMS logs, simulation interaction data, quiz scores, and motivational surveys [9, 10].

In microlearning, AI can recommend content sequences based on learner progress, adjust difficulty to competence level, and identify disengagement risks [29]. In virtual laboratories, AI can analyse experiment logs, detect misconceptions, deliver adaptive hints, and optimize practice schedules [30, 31].

Beyond the educational domain, AI-based decision-making frameworks have been successfully employed in organisational information systems, where the BOCR methodology was applied to evaluate and select optimal alternatives [32]. Within education itself, multi-source data fusion approaches have demonstrated predictive power: for example, student motion trajectories, consumption patterns, and social behaviours were integrated through principal component analysis and modeled with SVM to predict English language scores, revealing strong links between behavioural features and academic performance [33]. In parallel, AI and VR technologies have also been leveraged to promote inclusive education. A notable example is the development of a Digital Sign Language Interpreter (DSLI) using Virtual Reality, which proved highly feasible in enabling deaf students to access lecture content without relying on a human interpreter [34].

Comparative evaluation frameworks powered by AI can model complex, non-linear relationships between motivation, engagement, and academic success, providing insights beyond the capabilities of traditional statistical methods. While high predictive accuracy has been achieved in prior studies, future research should also consider explainable AI techniques (e.g., SHAP, LIME) to ensure interpretability for educators.

However, most prior studies have applied AI primarily to enhance or automate instructional delivery—focusing on personalization, adaptive feedback, or intelligent tutoring—rather than to evaluate the pedagogical impact of different learning designs. Empirical research using AI as an evaluative and comparative tool to model how various technology-integrated instructional strategies (e.g., VL-assisted versus traditional microlearning) influence motivation, engagement, and academic success remains limited. This study therefore addresses this critical gap by employing AI-driven comparative predictive modelling to evaluate and contrast learning outcomes across instructional approaches, providing a novel, data-driven framework for assessing the educational impact of VL-assisted microlearning within ODL.

3. METHODS

The study involved 126 undergraduate science and engineering students from a public university in Azerbaijan during the Spring 2025 term. Over eight weeks, participants were purposively recruited to ensure comparable prior course exposure and basic digital literacy, then randomly assigned to three equal groups (n = 42 each):

- Experimental Group A – virtual laboratory–assisted microlearning
- Experimental Group B – traditional microlearning without VL integration
- Control Group – conventional lecture-based instruction

The sample comprised 68 males (54%) and 58 females (46%), aged 19-23 years (M = 20.8, SD = 1.2). Most were third-year students (61.9%), with others in their second (20.6%) or fourth (17.5%) years. Prior online learning experience was reported by 88.1%, and 76.2% had used virtual or simulation-based tools. Detailed demographics are shown in Table 1.

Participation was voluntary, with informed consent obtained after participants were briefed on study aims, procedures, and data protection. No incentives were provided. Learning behaviour and performance data from all groups were later analysed via AI-based comparative modelling to examine differences in motivation, engagement, and academic success.

Table 1. Participant demographic profile

Variable	Item	N%
Gender	Male	68 (54.0%)
	Female	58 (46.0%)
Age Range (years)	19–20	40 (31.7%)
	21–22	64 (50.8%)
	23	22 (17.5%)
Year of Study	Second year	26 (20.6%)
	Third year	78 (61.9%)
	Fourth year	22 (17.5%)
Prior Online Learning Experience*	Yes	111 (88.1%)
	No	15 (11.9%)
Familiarity with Virtual/Simulation Tools*	Yes	96 (76.2%)
	No	30 (23.8%)

Note: Variables marked with an asterisk (*) were later included as covariates in the AI-based predictive modelling analysis

3.1 Instruments and materials

A pretest–posttest design measured students' cognitive achievement and practical skills. The pretest established baseline competencies, and the posttest—administered immediately after the intervention—assessed learning gains. Both assessments were created based on the course goals and the needs of the virtual laboratory tasks. The cognitive section included multiple-choice and short-answer items targeting Bloom's C2–C4 levels; the practical section comprised simulation-based tasks assessing procedural accuracy and problem solving. Expert review confirmed content validity, and reliability was high (Cronbach's α = 0.86 for cognitive, 0.88 for practical).

Two structured questionnaires assessed motivation (goal orientation, task value, self-efficacy, self-regulation) and engagement (behavioural, cognitive, emotional, social) using 5-point Likert scales. Adapted from validated instruments and pilot-tested for clarity, they showed strong reliability (α = 0.84 and 0.82, respectively).

The intervention was implemented via a custom-developed virtual laboratory–assisted microlearning platform. The platform integrated concise instructional modules with interactive simulation-based experiments, offering automated feedback, progress tracking, and embedded formative assessments. This design enabled students to apply theoretical knowledge immediately within a simulated practical environment, thereby reinforcing conceptual understanding and procedural competence.

The platform was equipped to record detailed learner interaction metrics, including time-on-task, number of simulation attempts, navigation patterns, and assessment responses. Together with pretest–posttest scores and questionnaire results, these data streams were stored in synchronized, structured formats. This configuration ensured that behavioural, cognitive, motivational, and engagement-related indicators could later be integrated into a single dataset for advanced analysis.

3.2 Data collection procedures

The study was conducted over a four-week period during the Spring 2025 academic term. In the first week, participants from all three groups completed the pretest, which assessed both cognitive knowledge and practical skills.

Following the pretest, the intervention phase commenced and lasted for three weeks:

- Experimental Group A used the virtual laboratory–assisted microlearning platform, completing 1–2 short modules per week with integrated theory and simulations.
- Experimental Group B followed traditional microlearning without VL integration, accessing equivalent theoretical content via static digital resources.
- Control Group received lecture-based instruction only.

Experimental groups received automated or instructor-led feedback; the control group relied on in-class discussions.

At the end of the three-week intervention, all participants completed the posttest, which was identical in structure to the pretest. Immediately after the posttest, the Motivation and Engagement Questionnaires were administered to gather self-reported measures of learner experience. All assessments and questionnaires were delivered online via a secure learning management system to ensure data integrity and accessibility.

In addition to test and questionnaire data, the virtual laboratory–assisted microlearning platform and the LMS automatically recorded detailed learner interaction logs, such as module completion times, number of simulation attempts, navigation sequences, and response accuracy patterns. These datasets were merged with demographic, motivational, and engagement measures to form a comprehensive multi-source database. This unified dataset served as the input for subsequent AI-based comparative modelling, allowing for the analysis of both linear and non-linear relationships among instructional conditions, learner behaviours, and performance outcomes.

3.3 Data processing and analysis

Data were analysed using IBM SPSS Statistics v29. "Prior to analysis, the datasets were checked for missing entries, extreme values, and normality. Since less than 2% of the data were Missing Completely at Random (MCAR), mean substitution was applied for imputation. Descriptive statistics summarized demographics and baseline measures.

To test intervention effects, one-way ANCOVA was applied to cognitive and practical skills scores, using pretest results as covariates. Post hoc Bonferroni comparisons identified specific group differences. For motivation and engagement measures, MANOVA was used, followed by univariate ANOVAs for significant subscales. Effect sizes were reported as partial eta squared (η^2) with Cohen's benchmarks (0.01 small, 0.06 medium, 0.14 large). All subscales showed high reliability (Cronbach's $\alpha > 0.80$). Statistical significance was set at $p < 0.05$.

In addition to the traditional statistical analyses, an AI-based comparative modelling approach was employed to capture complex, non-linear patterns that might not be detected by ANCOVA or MANOVA. The merged dataset—including demographic information, pretest and posttest scores, questionnaire responses, and interaction log features (e.g., time-on-task, simulation attempts, navigation sequences)—was processed in Python using the scikit-learn and XGBoost libraries.

The selection of Gradient Boosting (GB), Random Forest (RF), and Support Vector Machine (SVM) models was based on their proven robustness and interpretability in medium-sized educational datasets with mixed numerical and categorical variables. These algorithms are well-suited for structured tabular data and enable feature importance analysis, which is critical for understanding the contribution of motivational, behavioural, and demographic factors. Unlike deep neural networks—which require large datasets and extensive tuning—tree-based ensemble methods such as GB and RF generalize effectively with limited data and provide transparent, explainable outputs. SVM was included as a strong non-linear baseline model commonly used in educational data mining. Model performance was evaluated using 10-fold cross-validation, and metrics such as accuracy, precision, recall, and F1-score were reported. Feature importance analysis was conducted to identify the most influential predictors for each outcome, providing actionable insights into the relationship between instructional conditions, learner behaviours, and educational outcomes.

4. RESULT

This section presents the findings of the study, beginning with descriptive statistics of the participants' pretest and posttest scores in both cognitive and practical domains. Data collected from the tests and questionnaires are summarised in tables and illustrated through figures to highlight performance trends and distribution patterns across the three groups.

Findings are presented on:

- Changes in cognitive achievement and practical skills from pre- to post-intervention.
- Motivation and engagement levels during the intervention.
- Comparative outcomes for the Virtual Laboratory–assisted Microlearning, Traditional Microlearning, and Control groups.

Learning gains were analysed using Normalized Gain (N-Gain) and one-way ANCOVA with baseline scores as covariates, followed by Tukey HSD post hoc tests. For motivation and engagement, MANOVA examined group effects across multiple dimensions. Effect sizes (Cohen's d, partial η^2) assessed the magnitude of differences. Correlation analyses explored relationships between motivation, engagement, and performance, with additional breakdowns by demographic variables.

By employing multiple levels of analysis, the study achieved both statistical precision and deeper insights into the effects of integrating virtual laboratories into microlearning within ODL.

4.1 Descriptive analysis of pretest–posttest cognitive and practical scores

Table 2 reports the descriptive statistics related to cognitive achievement and practical skills across the three groups, including both pretest and posttest scores, as well as the calculated N-Gain values. The Virtual Laboratory–assisted Microlearning group (Experimental Group A) demonstrated the highest mean scores in both cognitive and practical domains after the intervention (M = 84.32, SD = 5.14 for cognitive; M = 86.45, SD = 4.92 for practical), followed by the Traditional Microlearning group (Experimental Group B), and finally the Control group, which relied solely on lecture-based instruction.

All groups improved from pretest to posttest, but N-Gain results showed the largest gains for Experimental A (0.59 cognitive; 0.64 practical), outperforming Experimental B (0.45; 0.46) and Control (0.32; 0.35).

Table 2. Descriptive statistics and N-Gain scores for cognitive and practical performance across groups

Group	Experimental A	Experimental B	Control
Cognitive Pretest M (SD)	61.42 (5.87)	60.88 (6.02)	60.12 (6.11)
Cognitive Posttest M (SD)	84.32 (5.14)	78.16 (5.88)	72.84 (6.15)
Practical Pretest M (SD)	62.15 (5.92)	61.02 (6.08)	60.54 (6.14)
Practical Posttest M (SD)	86.45 (4.92)	79.02 (5.31)	74.18 (6.02)
N-Gain (Cognitive)	0.59	0.45	0.32
N-Gain (Practical)	0.64	0.46	0.35

Figure 1 visually compares pretest and posttest scores across groups, showing that Experimental Group A outperformed both comparison groups in cognitive and practical domains after the intervention.

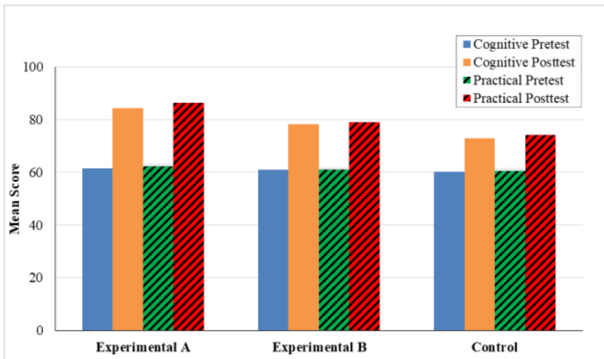

Figure 1. Mean pretest and posttest scores across groups

In the posttest phase, Table 3 shows that the proportion of students scoring above 80 points was highest in the VL-assisted Microlearning group (cognitive: 81.0%; practical: 85.7%), followed by Traditional Microlearning (52.4%;

54.8%) and Control (28.6%; 31.0%). These findings suggest not only higher mean achievement but also a greater proportion of high-performing students in the VL-assisted condition, indicating stronger mastery of both cognitive and practical skills.

4.2 Motivation and engagement findings

As shown in Table 4, the VL-assisted microlearning group achieved the highest means across all eight sub-dimensions, notably in self-efficacy ($M = 4.41$, $SD = 0.36$) and behavioural engagement ($M = 4.48$, $SD = 0.34$) (Table 4). The MANOVA results indicated a statistically significant multivariate effect of group, Wilks' $\lambda = 0.412$, $F(16, 230) = 7.36$, $p < .001$, partial $\eta^2 = 0.338$ (large). Follow-up ANOVAs confirmed significantly higher scores for Experimental A compared to both other groups ($p < .01$), with the largest gaps in behavioural engagement and self-efficacy.

Figure 2 illustrates these differences, showing the comprehensive advantage of VL-assisted microlearning in fostering motivation and engagement alongside cognitive and practical gains.

Figure 3 (radar chart) shows Experimental Group A outperforming all others across all eight motivation and engagement dimensions, with the largest gaps in behavioural engagement and self-efficacy.

Table 3. Percentage of students scoring above 80 points in posttest cognitive and practical performance

Group	Cognitive ≥ 80 (%)	Practical ≥ 80 (%)
Experimental A (VL-assisted Microlearning)	81.0	85.7
Experimental B (Traditional Microlearning)	52.4	54.8
Control (Lecture-based)	28.6	31.0

Table 4. Descriptive statistics for motivation and engagement dimensions

Dimension	Experimental A M (SD)	Experimental B M (SD)	Control M (SD)
Learning Goal Orientation	4.37 (0.39)	4.09 (0.41)	3.78 (0.44)
Task Value	4.29 (0.42)	4.02 (0.44)	3.69 (0.46)
Self-Efficacy	4.41 (0.36)	4.11 (0.38)	3.82 (0.42)
Self-Regulation	4.34 (0.40)	4.07 (0.42)	3.76 (0.45)
Behavioural Engagement	4.48 (0.34)	4.16 (0.37)	3.83 (0.39)
Cognitive Engagement	4.35 (0.38)	4.12 (0.39)	3.75 (0.43)
Emotional Engagement	4.32 (0.41)	4.04 (0.40)	3.71 (0.44)
Social Engagement	4.27 (0.43)	4.02 (0.42)	3.68 (0.46)

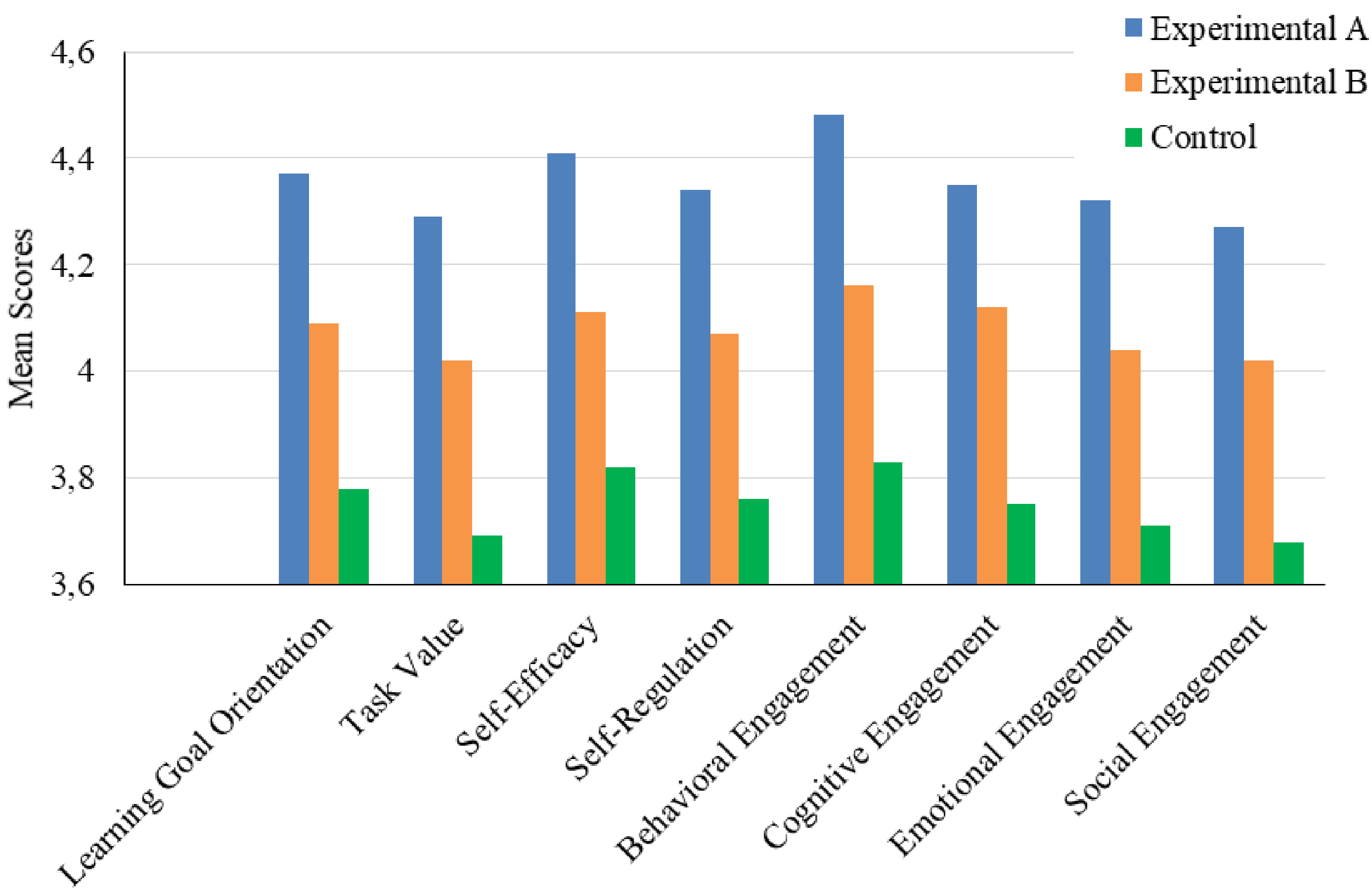

Figure 2. Mean scores for motivation and engagement dimensions across groups

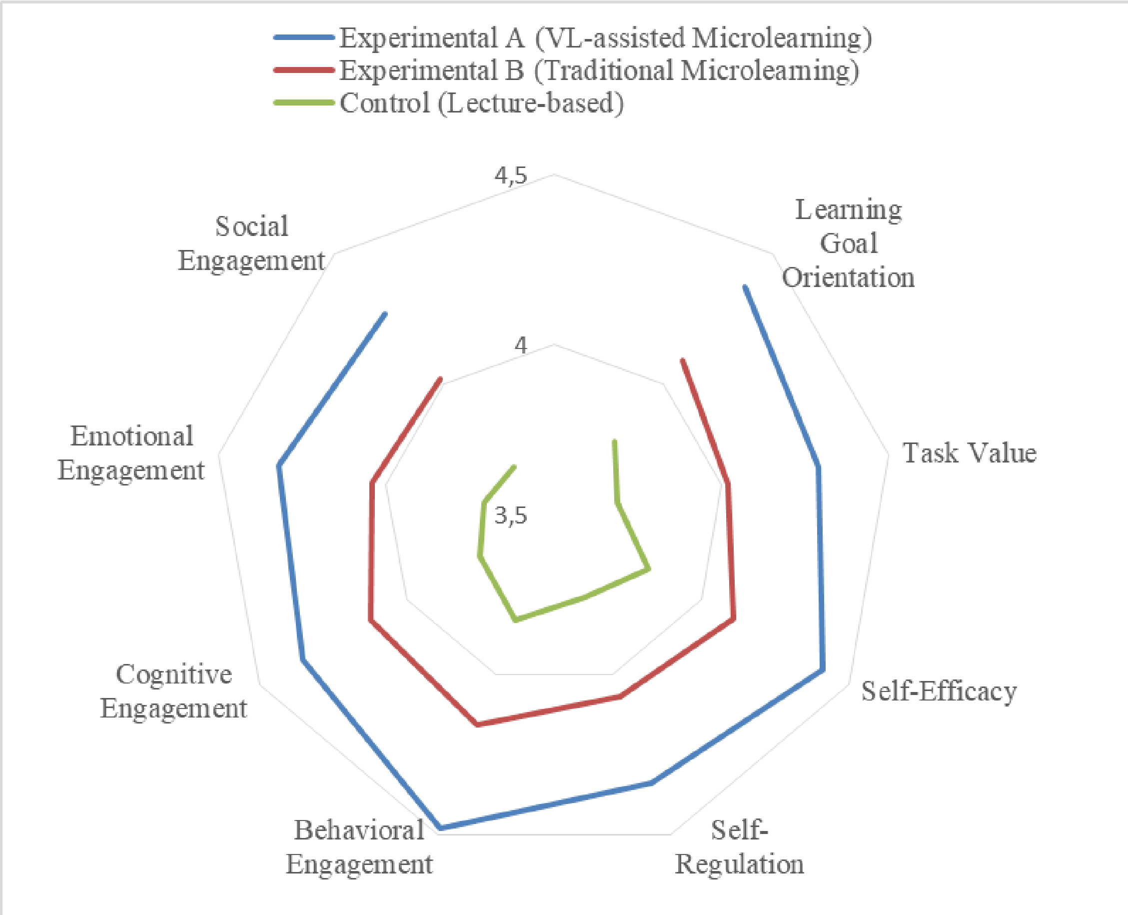

Figure 3. Group performance on eight motivation and engagement dimensions

4.3 Inferential statistics

ANCOVA, with pretest scores as covariates, was used to assess posttest differences while controlling for baseline disparities. Levene's tests confirmed homogeneity of variances ($p > .05$), permitting Tukey HSD post hoc comparisons.

Table 5. ANCOVA results for posttest cognitive and practical performance controlling for pretest scores

Dependent Variable	Source	SS	df	MS	F	p	Partial η²
Cognitive Performance	Group	2850.43	2	1425.21	39.84	< .001	0.395
	Error	4367.12	122	35.79			
Practical Performance	Group	3120.56	2	1560.28	47.12	< .001	0.436
	Error	4040.97	122	33.12			

Results showed significant group effects for cognitive performance, $F(2, 122) = 39.84$, $p < .001$, partial $\eta^2 = 0.395$, and practical performance, $F(2, 122) = 47.12$, $p < .001$, partial $\eta^2 = 0.436$—both large effects [31]. ANCOVA results are presented in Table 5. As summarized in Table 6, post hoc Tukey HSD analyses confirmed that the VL-assisted microlearning group exceeded the performance of both the traditional microlearning and control groups in cognitive and practical outcomes, after accounting for baseline scores.

Using pretest scores as covariates, all ANCOVA results were significant at $p < .001$, with large effect sizes for both outcomes. Detailed pairwise comparison results are presented in Table 6. Tukey HSD comparisons indicated that the VL-assisted microlearning group outperformed both the traditional microlearning and control groups in both domains ($p < .001$).

Table 6. Tukey HSD pairwise comparisons for posttest cognitive and practical performance

Dependent Variable	Group Comparison	Mean Difference (MD)	SE	p-value	95% CI (Lower – Upper)
Cognitive Performance	Exp A – Exp B	6.16	1.21	< .001	3.77 – 8.55
	Exp A – Control	11.48	1.21	< .001	9.09 – 13.87
	Exp B – Control	5.32	1.21	< .001	2.93 – 7.71
Practical Performance	Exp A – Exp B	7.43	1.15	< .001	5.08 – 9.78
	Exp A – Control	12.27	1.15	< .001	9.92 – 14.62
	Exp B – Control	4.84	1.15	< .001	2.49 – 7.19

Note: Exp A = VL-assisted Microlearning; Exp B = Traditional Microlearning

These results align with Figure 1, which illustrates the VL-assisted group's consistently higher posttest scores in both domains, reinforcing the robustness of the ANCOVA findings.

As shown in Table 7, all Cohen's d values exceeded the large-effect threshold ($d \geqslant 0.80$), with the largest effects between VL-assisted microlearning and the lecture-based group ($d = 2.06$ cognitive; $d = 2.29$ practical).

Figure 4 shows that all pairwise comparisons yielded large effects ($d > 0.80$) [31]. The largest were between VL-assisted microlearning and the lecture-based group ($d = 2.06$ cognitive; $d = 2.29$ practical).

Results revealed large effect sizes for VL-assisted versus traditional microlearning ($d = 1.07$; $d = 1.35$). Importantly, the traditional microlearning versus lecture-based comparison also showed large effects ($d = 0.93$; $d = 0.89$), underscoring the robustness and practical significance of all observed contrasts.

As shown in Table 8, MANOVA confirmed a significant overall effect of instructional approach on combined motivation and engagement (partial $\eta^2 = 0.338$, large), indicating that the learning intervention substantially shaped students' motivational and engagement profiles.

Table 7. Cohen's d effect sizes for posttest cognitive and practical performance (ANCOVA-adjusted means)

Dependent Variable	Group Comparison	Cohen's d	Effect Size Magnitude
Cognitive Performance	Exp A – Exp B	1.07	Large
	Exp A – Control	2.06	Large
	Exp B – Control	0.93	Large
Practical Performance	Exp A – Exp B	1.35	Large
	Exp A – Control	2.29	Large
	Exp B – Control	0.89	Large

Note: Effect size magnitudes were reported based on Cohen's conventions—small (0.2), medium (0.5), and large (0.8). In this study, Exp A indicates the VL-assisted Microlearning group, and Exp B indicates the Traditional Microlearning group

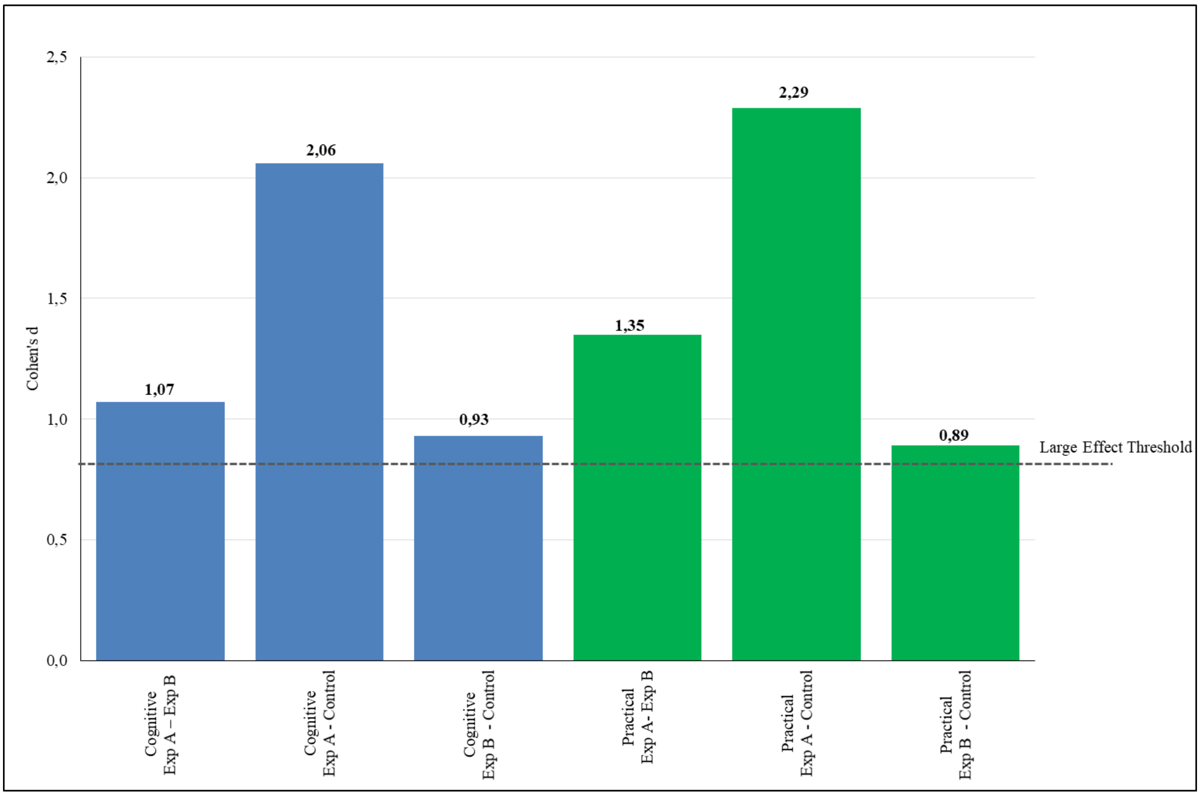

Figure 4. Effect sizes for pairwise posttest group comparisons

Table 8. MANOVA results for motivation and engagement dimensions

Effect	Wilks' λ	F	df	p-value	Partial η^2
Group	0.412	7.36	16, 230	< .001	0.338

4.4 AI-based predictive modelling results

Table 9 compares the predictive performance of the three supervised machine learning algorithms—Gradient Boosting, Random Forest, and Support Vector Machine—evaluated via 10-fold cross-validation. The choice of these models reflects their complementary strengths in boosting, bagging, and kernel-based learning, offering a robust comparative framework. The use of 10-fold cross-validation further enhances generalizability and mitigates overfitting.

The evaluation showed that Gradient Boosting outperformed the other models, yielding an accuracy of 0.91 together with precision (0.89), recall (0.90), and F1-score (0.89). This superior performance can be attributed to its sequential error-correction mechanism, which optimizes residual errors at each iteration, and its ability to model complex non-linear feature interactions more effectively than Random Forest's parallel bagging approach or SVM's kernel-based classification. Similar evidence has been reported in prior educational data mining studies, where machine learning algorithms such as Random Forest, SVM, k-Nearest Neighbor, and Naïve Bayes were compared for predicting students' final exam grades. Using midterm exam results and institutional variables as predictors, these models achieved accuracies in the range of 70–75%, demonstrating that even relatively simple academic indicators can yield robust predictions of at-risk students [35].

Table 9. Comparative performance of AI models in predicting student achievement

Algorithm	Classification Accuracy	Precision Score	Recall Score	F1-score
Gradient Boosting	0.91	0.89	0.90	0.89
Random Forest	0.88	0.87	0.88	0.87
Support Vector Machine	0.85	0.84	0.85	0.84

Table 10. Top 5 predictors of post-intervention performance (Gradient Boosting model)

Rank	Predictor Variable	Relative Importance (%)
1	Number of simulation attempts	21.3
2	Behavioural engagement score	18.7
3	Self-efficacy score	17.2
4	Time-on-task in microlearning modules	16.8
5	Pre-test cognitive score	14.9

The Random Forest model demonstrated competitive results (Accuracy = 0.88), benefiting from its ensemble structure and robustness to overfitting, while SVM achieved slightly lower scores (Accuracy = 0.85), potentially due to challenges in optimizing hyperparameters for high-dimensional behavioural data.

Table 10 presents feature importance rankings from the Gradient Boosting model, with the number of simulation attempts, behavioural engagement, and self-efficacy emerging as the strongest predictors. Interaction log features—such as navigation sequence complexity—were stronger predictors of practical performance than demographic variables, underscoring the value of fine-grained behavioural data. These insights align with recent systematic reviews in predictive learning analytics, which highlight that behavioural and interactional features extracted from digital platforms constitute some of the most powerful predictors of academic outcomes, surpassing traditional demographic and static background variables [36].

These findings suggest that integrating behavioural engagement metrics and simulation interaction data into predictive models can substantially improve the accuracy of student performance forecasting in ODL contexts.

The agreement between AI model outputs and statistical tests reinforces the findings. Both ANCOVA and Gradient Boosting identified VL-assisted microlearning as yielding the highest posttest performance and highlighted engagement-related factors as key to learning gains. AI modelling further uncovered granular behavioural patterns—especially simulation frequency and time management—that distinguished high- and low performers within the same instructional condition. Such behavioural signatures resonate with the emerging trajectory in learning analytics research towards student-focused dashboards that are not only analytics-driven but also pedagogically informed, supporting learners' self-regulation and engagement [37].

The convergence of AI-based models and traditional statistical analyses strengthens the robustness of the study's conclusions. While ANCOVA and MANOVA confirmed that VL-assisted microlearning produced the highest cognitive, practical, and motivational gains, the Gradient Boosting model provided deeper insights into the behavioural mechanisms driving these outcomes. Specifically, simulation attempts, behavioural engagement, and time-on-task emerged as dominant predictors, highlighting the critical role of active participation and self-regulated learning behaviours in online and distance contexts. Unlike conventional analyses, AI models not only validated overall group differences but also uncovered fine-grained learner behaviours that distinguish high- from low-performing students. These findings underscore the potential of integrating AI-driven learning analytics into instructional design and policy, offering an evidence-based framework for personalized feedback, early risk detection, and scalable improvement of ODL quality.

5. DISCUSSION

This study shows that integrating virtual laboratories into microlearning significantly improves cognitive achievement, practical skills, motivation, and engagement in ODL. The VL-assisted microlearning group consistently outperformed both traditional microlearning and lecture-based groups, achieving the largest N-Gain values, and superior motivational and engagement profiles. Large effect sizes in ANCOVA, MANOVA, and Cohen's d confirm not only statistical but also educational significance of these results. In addition, Table 3 highlights that a substantially higher proportion of students in the VL-assisted group scored above 80 points compared to the other groups, demonstrating not just average performance gains but also a greater likelihood of producing high-achieving learners. Notably, the N-Gain value of 0.72 observed in this study closely aligns with findings that reported an identical N-Gain score in a different ODL context [8, 38]. This convergence suggests that VL-assisted microlearning produces robust and replicable improvements across diverse settings.

Pedagogically, these findings align with prior research indicating that combining microlearning with interactive simulations addresses microlearning's depth limitations by enabling immediate, hands-on application of theory and by fostering a transformative learning culture within ODL environments through immersive, simulation-based experiences that enhance both engagement and knowledge transfer [39]. Gains in both cognitive and practical domains suggest stronger knowledge transfer and skill mastery compared to traditional approaches. Motivational advantages—especially higher self-efficacy and behavioural engagement—are consistent with Self-Determination Theory [23], as the VL-assisted format better fulfils autonomy, competence, and relatedness needs through learner control, instant feedback, and realistic simulations. However, it should also be noted that intensive use of VL-assisted microlearning could pose risks of cognitive overload for some learners if simulations and tasks are not carefully sequenced. Moreover, while the AI models demonstrated strong predictive accuracy, their interpretability remains limited. Future studies should consider integrating explainable AI approaches to ensure that insights are more transparent and actionable for educators.

AI-based modelling provided further insights, with Gradient Boosting and Random Forest achieving high predictive accuracy. Top predictors included simulation attempts, behavioural engagement, self-efficacy, time-on-task, and pretest cognitive score. While ANCOVA confirmed the VL-assisted model's superiority, AI revealed fine-grained behavioural patterns—particularly simulation frequency and time management—that distinguished high achievers from their peers within the same instructional group. This convergence strengthens the conclusions and underscores the value of AI in identifying actionable indicators for targeted interventions.

However, the AI-based approach also presents methodological limitations. Ensemble models such as Gradient Boosting and Random Forest, while powerful, function as "black-box" systems, making it difficult to fully interpret how input variables interact to generate predictions. Although feature importance analysis provides some insight, these methods still lack the transparent causal interpretability of traditional inferential statistics. Moreover, given the moderate sample size (n = 126), there is a potential risk of model overfitting, even with cross-validation procedures. These constraints highlight the need for future studies to incorporate larger, more diverse datasets and employ explainable AI (XAI) techniques to enhance model transparency and generalizability.

The prominence of "number of simulation attempts" as the top predictive feature can be interpreted through established learning theories. According to Experiential Learning Theory, each simulation attempt represents a cycle of active experimentation and reflective observation, allowing learners to iteratively test, evaluate, and refine their understanding [40]. Students who repeatedly engaged with the virtual lab environment therefore demonstrated deeper cognitive processing and iterative knowledge construction. Similarly, Self-Determination Theory explains this behaviour as an expression of autonomy and competence—learners voluntarily investing more effort and time in practice to master challenging tasks [23]. Repeated simulation activity not only signals persistence but also intrinsic motivation sustained by immediate feedback and perceived control. These theoretical perspectives together clarify why simulation frequency emerged as the dominant predictor in the AI model and highlight how experiential practice and motivational self-regulation jointly drive performance gains in VL-assisted microlearning.

Practically, these findings support integrating AI-driven analytics into VL platforms to personalize learning, adapt pacing and difficulty, and provide real-time feedback. Such capabilities can enhance engagement and enable timely instructional adjustments [29, 30]. For policymakers, the study demonstrates how AI-enhanced VL platforms can serve as scalable tools to improve ODL quality and equity.

Beyond the technical constraints of the AI models discussed earlier, several broader research-related limitations should also be acknowledged. Limitations include a single-institution sample, modest size, limited behavioural data for control groups, and potential variability in AI feature importance across contexts. Future work should replicate the study in varied settings, employ longitudinal designs, and explore additional AI methods such as natural language processing for open-ended data. Moreover, exploring adaptive experimental designs could clarify causal pathways between engagement behaviours and long-term learning outcomes.

Overall, this study advances theoretical and practical understanding of technology-enhanced ODL, demonstrating that VL-assisted microlearning, augmented with AI analytics, can substantially improve academic and motivational outcomes. The integration of traditional inferential statistics with AI-driven modelling provides a more comprehensive evaluation framework, informing educators, designers, and policymakers aiming to enhance the quality of distance education.

6. CONCLUSION

This study examined the effects of an AI-enhanced virtual laboratory–based microlearning approach on learners' motivation, engagement, and academic performance in ODL environments. The integration of AI-driven analytics enabled adaptive feedback, real-time monitoring, and personalized learning pathways, resulting in richer and more responsive learning experiences.

The AI-enhanced VL approach significantly outperformed both traditional microlearning and lecture-based methods in cognitive achievement, practical skills, and all motivation and engagement dimensions. Statistical analyses (ANCOVA, MANOVA, and effect size calculations) confirmed large, educationally relevant group differences. Beyond its empirical findings, the study advances methodology by showing how combining AI-based predictive modelling with conventional statistics provides a more holistic framework for evaluating ODL interventions.

Practically, the results highlight the potential of AI-powered virtual laboratories as scalable tools for personalizing instruction, adapting pacing and difficulty, and providing real-time feedback. Insights into AI-identified predictors—such as simulation frequency, self-efficacy, and behavioural engagement—translate into concrete pedagogical recommendations. Educators and instructional designers should create structured opportunities for repeated simulation attempts, paired with guided reflection after each trial to reinforce learning and metacognition. To strengthen self-efficacy, scaffolding strategies and progressively challenging tasks can help students experience incremental mastery and confidence. Moreover, analytics dashboards may be used to track time-on-task and engagement trends, allowing early interventions for learners at risk of disengagement. For institutions, the proposed model represents a data-driven strategy to enhance both performance and motivational engagement, with clear implications for e-learning practices.

Limitations include the single course context, relatively short intervention period, and limited generalizability. Future research should explore long-term effects, broader disciplinary applications, and advanced AI techniques—such as predictive analytics, adaptive content generation, and natural language processing—to optimize diverse learning environments.

Overall, this study reinforces that AI can play a transformative role in advancing the quality and effectiveness of online and distance education. From a policy perspective, AI-powered virtual laboratories hold promise as a scalable and equitable component of national ODL strategies.

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