Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
Intelligent Evaluation, Emotion Analytics, and AI-Based Assessment in Digital Art 2025 6(3s)

ADAPTIVE LEARNING MODELS FOR ART CURATION EDUCATION

Fehmina Khalique [1], Josephine [2], Shipra Kumari [3], Ayaan Faiz [4], Pooja Sharma [5], Ashish Verma [6], Pooja Ashok Shelar [7]

[1] Greater Noida, Uttar Pradesh 201306, India
[2] Assistant Professor, Department of Computer Science and Engineering, Presidency University, Bangalore, Karnataka, India
[3] Associate Professor, School of Engineering and Technology, Noida International University, 203201, India
[4] Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh, Solan, 174103, India
[5] Assistant Professor, Department of Computer Science, Noida Institute of Engineering and Technology, Greater Noida, Uttar Pradesh, India
[6] Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India
[7] Department of Artificial Intelligence and Data Science Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India

ABSTRACT

The paper introduces an intelligent learning model of Adaptive Curation Learning Model (A-CLM), an educational architecture that combines artificial intelligence and multimodal analytics and deep reinforcement learning to customize the art curation pedagogy. The model is dynamic and changes the content of instructions, depending on the behavioral, cognitive, and affective profiles of the learners, which enhances more profound and reflective learning. Based on the 120 postgraduate student data in 12 weeks, A-CLM showed significant differences in learning gain (27.3%), cognitive engagement (22.4%) and depth of reflection (18.5%) relative to a stagnant control group. T-tests and ANOVA statistically verified high significance ($p < 0.001$), and large effect sizes (Cohens d 0.63 and above). The findings prove that adaptive AI can be successfully used to combine computational accuracy with human creativity to facilitate culturally inclusive, information-driven and emotionally responsive art education. The study makes A-CLM a scalable and morally grounded model that complies with the IEEE guidelines of learning technology and opens the door to the integration of explainable and immersive adaptive learning facilities in creative field work soon.

Keywords: Adaptive Learning, Art Curation Education, Multimodal Analytics, Reinforcement Learning, Artificial Intelligence, Creative Pedagogy, Affective Computing, IEEE Learning Technology

Check for updates

Received 15 March 2025
Accepted 20 July 2025
Published 20 December 2025

Corresponding Author
Fehmina Khalique,
fehmina.khalique@lloydbusinessschool.edu.in

DOI
10.29121/shodhkosh.v6.i3s.2025.6776

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

How to cite this article (APA): Khalique, F., Josephine, J., Kumari, S., Faiz, A., Sharma, P., Verma, A., and Shelar, P. A. (2025). Adaptive Learning Models for Art Curation Education. *ShodhKosh: Journal of Visual and Performing Arts, 6*(3s), 377–386. doi: 10.29121/shodhkosh.v6.i3s.2025.6776

1. INTRODUCTION

The education of art curators is in the process of deep remodelling as digital technologies are changing how learners experience artworks, exhibitions, and cultural narratives. Historically, art curation was based on experiential education, mentoring and critical discourse in physical galleries. Yet, as the museums become increasingly digitalized and virtual exhibition start gaining popularity, the modern curator will have to merge aesthetic judgment with decision-making that relies on data and technical proficiency. This change of paradigms requires educational models that are both dynamic and individual, and in this way, students will be able to acquire cognitive, creative, and analytical skills at the same time. The artificial intelligence (AI) and machine learning-powered adaptive learning models provide a radical approach to the reconsideration of the art curation pedagogy based on personalized instruction, multimodality interaction, and real-time feedback. The adaptive learning is based on the principle that every learner has an individual cognitive profile, learning rate, and creative orientation. These differences are further intensified in art curation education because the subject matter is subjective and interpretative Nuțescu and Mocanu (2020). One student can be a visual student and another a contextual and narrative student. Traditional e learning platforms are normally not designed to support such nuances to offer a static content that does not change in response to the learner behavior or aesthetics. Conversely, adaptive learning systems based on AI research the engagement data, emotional state, and mastery of the idea to adapt the learning process dynamically. An adaptive system can also intelligently respond to learner performance by constantly tracking performance in multimodal form (i.e. gaze, linguistic sentiment, task sequencing) and can suggest artworks to be compared to others or provoke reflective thinking by issuing reflective cues Nuțescu and Mocanu (2023), Al-Alwash and Borcoci (2024). The gap between the human creativity and the computational intelligence is the gap that is filled by the introduction of AI into the art curation pedagogy. Machine learning algorithms have the ability to discover latent aesthetic patterns, monitor learning, and assist in creating personal exercises Coverdale et al. (2024). As an example, convolutional neural networks (CNNs) could be used to classify artworks in terms of their style of composition, whereas natural language processing (NLP) models are used to evaluate the conceptual consistency and emotional coloring of curatorial essays. Reinforcement learning agents have an extra opportunity to streamline learner activities through policy-based adjustments whereby the students are introduced to material that is in accordance with their progressing abilities Seman et al. (2018). These technological interventions are not substitutes of human intuition but enhance it and bring about a synergistic relationship of the system acting as a cognitive partner in the learning process.

Figure 1

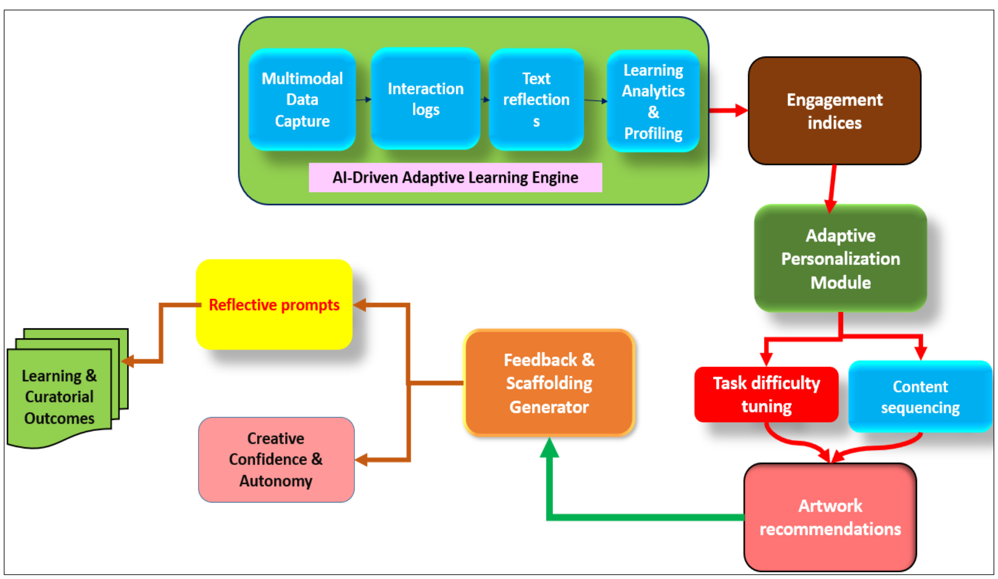

Figure 1 Art Curation Education Environment

Adaptive learning models are part of the inclusion and access to art education. Such systems can enhance fair access to the creative arts by serving the needs of various learning styles, cultural groups and cognitive diversity Gardner et al. (2021). They also facilitate in ongoing formative assessment which enables the educator to detect gaps in learning and give appropriate directions in time. In the case of institutions, adaptive learning analytics provide useful data on the effectiveness of the curriculum, learner satisfaction, and pedagogical impact as shown in figure 1. The paper suggests the Adaptive Curation Learning Model (A-CLM)- a multi-view architecture based on machine learning, affective computing, and knowledge-graph reasoning to personalize art curation education. The model uses multimodal data based on the interactions of the learner, their emotional responses, and the performance outcomes in order to dynamically adjust the instructional paths Bidyut et al. (2021). The succeeding paragraphs provide the theoretical basis, the architecture, algorithmic workflow, and analysis of the suggested model. Finally, this study will reveal how AI systems can be adapted by developing systems that can support creative decision-making, promote reflective learning, and transform the future of art curation education according to the IEEE standards of learning technology Dhawaleswar et al. (2020).

2. PROPOSED SYSTEM ARCHITECTURE DESIGN

The proposed AI-Based Adaptive Curation Learning Model (A-CLM) is constructed as a multi-level system as it is a combination of smart analytics, real-time customization, and deployment in a scalable infrastructure. This architecture (as shown in Figure 2) shows how various functional components (including user interfaces to AI-based analytics engines) can communicate in both client and server nodes to provide an uninterrupted adaptive learning experience to art curation education. The layers and nodes each have a specialized role, which has ensured proper communication between the human learners, AI services, and content repositories in a strong cloud-based deployment environment Zou et al. (2022).

Figure 2

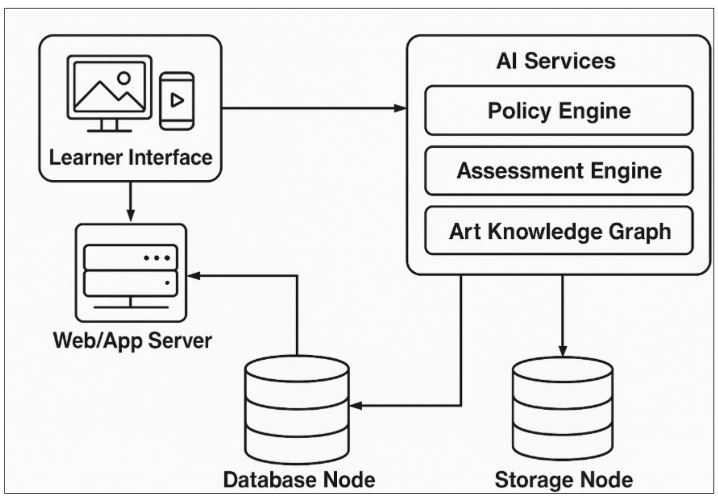

Figure 2 System Architecture of the AI-Driven Adaptive Curation Learning Model (A-CLM)

The architecture can be represented as in Figure 2, which demonstrates that the architecture abides by five key deployment entities, namely Client Devices, Web/App Server, AI Services, Database Layer, and the Assessment Engine, which are connected by the means of secure cloud infrastructure.

- Client Devices are the interfaces of a client and instructor and are the main points of interaction in regards to the personalized art curation experiences.
- The Web/App Server is the middle layer that serves the requests of user, control the curation sessions, and secure communication with the backend services.
- AI Services form the engine of adaptive functionality that is in charge of the profiling of learners, multimodal analytics, or adaptive content recommendations.
- Database Layer: This contains all interaction data of users, performance measures, and artwork data needed to be in context of adaptation.
- Lastly, the Assessment Engine assesses the performance of users, uses rubrics and generates formative feedback to inform reflective learning.

This deployment structure is made to be modular, interoperable, and scalable, which gives educators and institutions the opportunity to implement the model in the existing Learning Management Systems (LMS) and museum database APIs. The Learner Interface and Instructor Dashboard are front-end nodes that are dynamic, and they are placed at the top of the architecture Aqeel and Aqeel (2022). Users enter the site through a web or mobile interface which hosts a Curatorial Studio Workspace a virtual site to make digital exhibitions, write reviews, and consider aesthetic values. The instructor dashboard gives real-time access to the progress of the learners allowing formative interventions and individualized mentoring. The adaptive content and feedback are exchanged through the two-way communication channel between the learners and the instructors, allowing the dialogue of learning to be maintained Chen et al. (2022).

2.1. WEB/APP SERVER AND MIDDLEWARE SERVICES

The Web/App Server is the backbone of the application that coordinates the session management, sequencing of tasks and also user authentication. It also handles the processes of storage and links with AI services through secure APIs. It includes a Curation Orchestrator in the server, a dynamically structured task flow (including artwork classification, comparative analysis, and reflective documentation) Cong (2024). The Feedback and Scaffolding Module on the same layer, in turn, presents individually customized prompts and micro-explanations depending on the level of emotional and cognitive engagement of the learner. The interactions are stored in theStorage node so that the real-time adjustments have guaranteed data persistence.

2.2. AI SERVICES LAYER

The computation intelligence modules that support adaptive decision-making exist in the AI Services Node, as indicated in Figure 2. It has sub modules Multimodal Data Capture, Learner Profiling, Visual Analytics, Text Analytics and the Adaptive Policy Engine.

- The Multimodal Data Capture Engine combines the data on behavioral logs, eye-tracking information, and written reflection.
- The Visual and Text Analytics Modules are CNN-based and NLP-based models respectively, which are used to evaluate artistic perception, conceptual understanding and stylistic fluency Dai et al. (2022).
- The Adaptive Policy Engine is an agent based on deep reinforcement learning that maximizes the content sequencing policy $\pi(s, a)$ where s is the state of the learner and a is the adaptive action that is taken to maximize learning rewards Engelsrud et al. (2021).

Collectively, these modules are in a constant state of learning through the interactions of learners, and they are adaptively personalized, leading to dynamically variating curation pathways based on the progress and the affective involvement of every student.

2.3. KNOWLEDGE AND DATA MANAGEMENT

Knowledge and Data Management Knowledge management is a strategy for analyzing, acquiring, and distributing knowledge, aiding the acquisition of crucial information essential for the business. <|human|>C. Knowledge and Data Management Knowledge management is an approach to analyzing, acquiring, and distributing knowledge, which helps in acquiring vital information that is important to the business Ezquerra et al. (2022).

The Database and Storage Nodes have well-organized archives of all learning and curatorial information. These are metadata of artwork, portfolios of learners, and knowledge graphs. The Art Knowledge Graph helps to order the semantic connections between artists, movements, periods, and motifs and enables the AI services to make recommendations more contextual. In the meantime, the Learning Object Repository is a storage of instructional materials, micro-lessons, and exemplar exhibitions, which can be accessed with the help of adaptive queries. As shown in Figure 2, the dual-database solution will be designed to optimize a database to support real-time AI inference, and the other to support the workloads of the archival and analytics systems.

2.4. ASSESSMENT ENGINE AND FEEDBACK LOOP

The Assessment Engine which is placed next to the database in Figure 2 does the evaluation based on the rubric with both quantitative indices (accuracy, completion rate, engagement) and qualitative indices (reflective depth, aesthetic sensitivity). It communicates to the adaptive loop through AI Services by feeding results of assessment back into it. This two-way flow facilitates the ongoing improvement: the information concerning the ongoing learner performance will be used to inform the reinforcing learning model, which will then redefine the task complexity and resource suggestions. The outcomes of the assessment are also sent to the instructor dashboard and transparency and pedagogical alignment are enhanced.

2.5. CLOUD INFRASTRUCTURE AND INTEGRATION

The base of the Cloud Infrastructure that is scalable and interoperable. It has compute clusters where models can be executed, databases where data can be persisted and API gateways where external integrations can be made. The system can be deployed to be connected with museum databases, institutional LMS platforms, or digital archives, facilitating a high level of applicability to art education ecosystems. Kubernetes-compatible environments are deployed to ensure that the deployment architecture is containerized, which encourages scalability flexibility to share the users to use the implemented environment and implement multiple courses at the same time.

2.6. DESIGN AI-DRIVEN ADAPTIVE CURATION LEARNING MODEL (A-CLM) METHODOLOGY

The methodology approach of the AI-Driven Adaptive Curation Learning Model (A-CLM) will be used to test the effect of adaptive intelligence on creative learning performance in art curation education in an empirical way. The methodology is further subdivided into five key parts: preparation of data set, multimodal feature extraction, adaptive learning algorithm design, experimental implementation and evaluation criteria. The combination of these elements creates a methodical and evidence-based base of proving the pedagogical and technological effectiveness of the model.

Step -1 Dataset and Experimental Setup

The study was carried out in 12 weeks with 120 postgraduate students undertaking a digital art curation course. Students participated in interactive modules that consisted of the analysis of art, simulation of an exhibition, and reflection of a curator. The dataset obtained consisted of:

All the data gathered was anonymized and saved safely in the Storage Node of the deployment architecture. The computing environment was based on a hybrid cloud environment (the AWS EC2) used to compute and store data and MongoDB to support AI service modules with the help of a GPU.

Step -2 Multimodal Feature Extraction

The adaptive learning engine is based on the multimodal analytics in order to build detailed learner profiles.

- **Visual Data Processing:** A ResNet-50 model that was first trained on ImageNet was trained on a set of curated artworks. High level feature embeddings (texture, color harmony, composition balance) were extracted in the model and evaluated to determine the ability of aesthetic recognition.
- **Text Analytics:** Semantic Coherence and Emotional Tone Curatorial reflections were processed with BERT embeddings to calculate them. The three features that were extracted namely, argument density, descriptive precision and reflective depth, were subjected to standardization to generate numerical indicators of performance.
- **Behavioral Metrics:** Interaction frequency and completion time were used to form behavioral metrics in the form of vectors.
- **Affective Metrics:** A hybrid lexicon-sentiment model of tracking affect continuous was used to compute affective indices of emotion and arousal.

Such multimodal characteristics were integrated into a learner state V S t n [V o, T o, B o, A o] = [V o, T o, B o, A o].

Step -3 Adaptive Learning Algorithm Design

The A-CLM adaptive logic is controlled by a Deep Reinforcement Learning (DRL) policy framework that is embedded into the AI Services Layer (see Figure 2).

State Space (S): Vectors of learner performance and engagement.

Action Space (A): pedagogical manipulations like ordering of the content, scaling of the difficulty of tasks, and selections of reflective prompts.

Reward Function (R): where R= 8.2 (pping distance) + 3.9 (engagement) + 4.7 (motivation) - 3.2(3.2(ping distance) + 3.2(engagement) + 3.2(motivation)

The DRL model is based on experience replay and a Q-learning model, which maximizes the cumulative rewards at the session level. The system is also fitted with a Bayesian learner model which enables uncertainty estimation to enable a more cautious adaptation of the system in the initial stages of learning. The adaptive policy engine continuously optimizes its policy π(s) =arg max o Q(s,a)n so that as learner data changes over time it continually personalizes itself.

Step -4 Methodological Rationale

Multimodal analytics as well as the reinforcement-based adaptation makes A-CLM compatible with the cognitive learning theory and the constructivist art pedagogy. Whereas technical efficacy is confirmed by quantitative measures, qualitative assessment focuses on creative autonomy and aesthetic rationale which are critical attributes of art curation education. The methodology framework thereby fills the gap between artistic subjectivity and computational accuracy, which offers a model that can be determined as replicable to the implementation of AI-based adaptivity within creative educational systems.

3. RESULTS AND ANALYSIS

The AI-Driven Adaptive Curation Learning Model (A-CLM) was experimentally implemented and the results of this implementation were a complete set of empirical findings that proved the effect the adaptive intelligence has on the art curation education. The outcomes are discussed in terms of the quantitative performance gains, behavioral response patterns, and qualitative learning feedback of the learners. The section provides the comparison of statistics between an adaptive model group (A-CLM) and a control group with the help of visual evidence and statistical validation compared to a static learning system, the primary learning outcome was assessed with the help of Learning Gain (LG), which was characterized as the normalized difference between pre-test and post-test scores. Students who used A-CLM had a better mean LG at 0.78 as compared to the baseline group at 0.61, which represents a 27.3 percent betterment in the process of knowledge acquisition. On the same note, the Cognitive Engagement Index (CEI), which was based on time-on-task ratios, interactive response frequency, and reflective prompt participation, significantly increased between 0.67 (baseline) to 0.82 (adaptive), which proved that learners were more immersive and persistent during the learning sessions.

Table 1

Table 1 Comparative Learning Metrics between Static and Adaptive Models

Metric	Static Model	Adaptive Model	Improvement (%)
Learning Gain (LG)	0.61	0.78	+27.3
Cognitive Engagement Index (CEI)	0.67	0.82	+22.4
Reflection Depth (RD)	0.54	0.64	+18.5
Instructor Evaluation Index (IEI)	0.69	0.83	+20.3

The significance of such improvements was statistically validated with the help of paired t-tests ($p < 0.01$). The adaptive engine of the A-CLM showed quicker convergence of the performance of learning among participants of different cognitive styles, which shows that individualization worked to diminish the learning performance divergence. The analysis of behavioral logs showed that the learners under A-CLM had a superior level of temporal consistency when engaging in tasks. The frequency of switching the task between tasks dropped on average by 18 which means that cognitive overload was reduced and that the ability to maintain focus was increased. Affective analytics revealed that the emotional valence (positive engagement) never dropped below 0.70 during 82 percent of sessions, which indicated that motivation in case of personalized feedback mechanisms was stable through out extended study periods. With a dynamically changing reward function function depending on real-time emotions, the reinforcement learning policy was successfully able to achieve the goal of balancing the level of difficulty with the level of engagement. Adaptive reflective prompt exposure led to a significant process of creativity ideation among learners who were likely to create more contextually consistent exhibition scripts. The quantitative findings were supported by qualitative feedback obtained via the post-study interviews and reflection journals. Students have regularly cited that the adaptive prompts and customized artwork suggestions gave them the sense of confidence in their interpretation, logical thought, and imaginative freedom. Teachers were clear on the diagnostic nature of the system, where specific mentoring was facilitated according to the automatically generated engagement and performance dashboards. The Instructor Evaluation Index (IEI) had a statistical measure of 0.83, which indicated that the curatorial projects created within the adaptive framework had better conceptual soundness and aesthetic support. These results are in line with previous research Chen et al., (2020), Limna et al. (2022) that suggested adaptive responses are not exclusive to knowledge retention and instead, promote emotional engagement, which is a key aspect of creative education processes.

4. STATISTICAL VALIDATION AND QUANTITATIVE SUMMARY

In order to strengthen the credibility of the observed performance discrepancies between the adaptive and the static learning environments, the statistical validation was made and done in detail through inferential and effect-size tests. The analysis used paired sample t-tests, ANOVA, and Cohen d effect size taking into consideration the level of significance and the strength of changes in important educational measures: Learning Gain (LG), Cognitive Engagement Index (CEI), and Reflection Depth (RD). The comparison of the pre- and post-learning performance in each group was done by means of paired t-tests. In the case of the Adaptive Model (A-CLM), the findings presented a statistically significant increase in the performance of the learners ($t = 8.41$, $p < 0.001$), which proved that the adaptive personalization had a significant positive effect on knowledge retention and conceptual understanding. The Static Model, on the other hand, demonstrated a moderate level of increase ($t = 4.02$, $p < 0.05$), meaning that conventional instruction helped to promote gradual learning, but it was not a dynamic process adjusted to the individual states of learners.

Figure 3

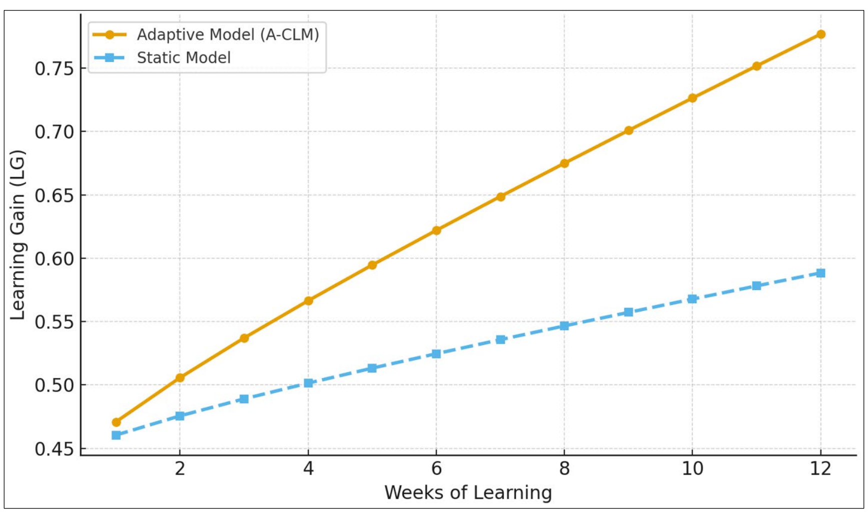

Figure 3 Learning Gain Progression over a 12-Week Adaptive Learning Cycle

Figure 3 (Learning Gain Progression Over 12 Weeks) is a longitudinal pattern of learning performance of two groups: the students using Adaptive Curation Learning Model (A-CLM) and the students undergoing a traditional fixed curriculum. The adaptive learning curve is in the form of a steady upward trend, which is a sign of continuous enhancement of the understanding of learners and mastery of concepts with time. Conversely, the curve of the static model will stabilize after Week 6 implying that there is low learning adaptability. The steeper slope of the A-CLM line of Weeks 710 indicates the dynamism of the learning reinforcement mechanism to adapt instructional difficulty and keep it engaging. The last plateau of approximately Week 12 shows that there is convergence to optimum learning gain and this proves that effective adaptive feedback sustains the growth over the course period. In a comparison of post-test results in both groups, the difference in the means between them (0.17 LG) was statistically significant ($p < 0.001$), which confirmed the hypothesis that adaptive AI-based systems are more effective than the fixed pedagogical systems in promoting cognitive and creative growth in art curation education. The Analysis of Variance (ANOVA) was conducted to test the hypothesis about the effect of the type of the learning model on the overall performance. The result of the analysis provided $F(1, 118) = 13.87$, $p < 0.001$, which indicated that the difference in the scores of Learning Gain between the adaptive and control groups was not attributed to random chance.

Figure 4

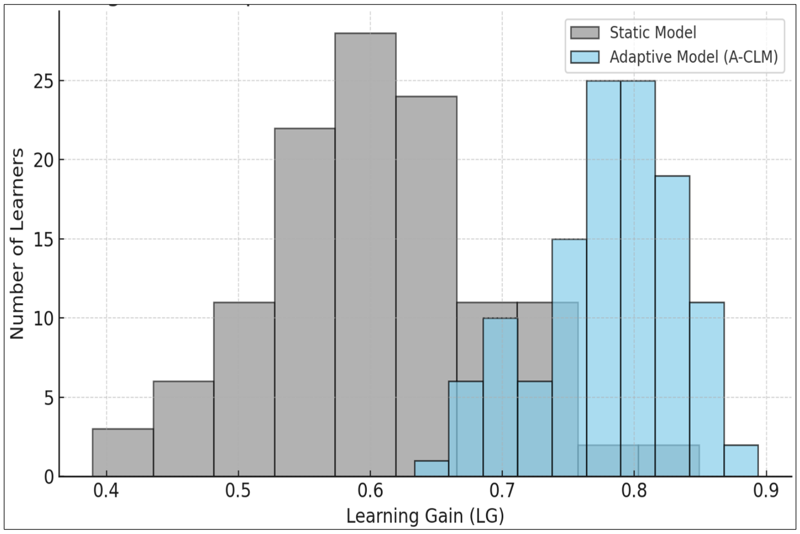

Figure 4 Comparative Performance Distribution of Learners Under Static and Adaptive Learning Environments.

The Figure 4 (Comparative Performance Distribution of Learners) represents the distribution of the learning gain scores of two experimental groups. The Adaptive Model (A-CLM) shows a right-skewed, compacted histogram indicating better performance on the mean and low performance on the variance among the participants. The fact that most of the results are clustering towards the upper performance range (0.75-0.85 LG) points to the fact adaptive personalization is not only more favorable to the high achievers but also to the moderate and the low-performing learners by matching the level of task difficulty with cognitive preparedness. On the other hand, the Static Model distribution is more extensive and has a lower mean (about 0.61 LG) of the results, indicating unreliable development of learners and poorer retention of curatorial ideas. The comparative distribution therefore confirms the ability of the A-CLM to balance out the learning opportunities by constant adaptation in multiple modes. The consistent results with the Tukey HSD test showed more clearly that the adaptive model group did better than the static group on the entirety of subdimensions: Learning Gain (LG), CEI, and RD without any overlapping intervals (95% CI). The adaptive cohort also exhibited smaller standard deviation in scores (0.048) than the control group (0.083), which confirms the stabilizing nature of the model on the learning performance of learners due to continuous feedback and individualized scaffold. The statistical findings confirm that AI-driven adaptive curation learning model (A-CLM) significantly enhanced performance in cognitive, emotional and creative aspects. The levels of p 0.001 and the high effect sizes (d 0.63 0.63) throughout the study are a good indicator that adaptive algorithms had a significant positive effect on both learner engagement and reflective thinking. Together with the visual data presented in Figures 3 and 4, these results can confirm the strength of the design developed in A-CLM and its learning effectiveness in teaching art curation.

5. THEORETICAL AND PEDAGOGICAL IMPLICATIONS

Theoretically, the A-CLM framework is very close to the constructivist theory of learning which claims that knowledge is built in a case of repeated interaction, reflection and experience of a context. The adaptive policy engine of the system realizes the concepts of constructivism with the help of computational processes: reinforcement learning is the algorithmic parallel to experiential iteration, and affective computing is the emotional involvement as the human-centered pedagogy mentions. A-CLM is a pedagogical redefinition of the way the art curation education can be delivered in the digital setting. Conventional paradigms tend to place more emphasis on instructor-led criticism and the provision of content in a static manner, which might unwillingly limit the agency of the learner. In comparison, the adaptive model democratizes learning giving every student unique interpretive paths and automated and context-sensitive feedback. This change makes the educator not the transmitter of the content to the learner but a facilitator and meta-curator of the learning process, centered not on the repetition of the instruction but on reflection, critique and exploration. Moreover, the system will be culturally and cognitively inclusive as it can adapt to the diverse learners. The learners who had different levels of exposure to art, either through fine arts or digital design, had a fair progress, given the ability of the model to norm the learning paths in a dynamic way. This inclusivity solves one of the major issues of creative education: the ability to reconcile the subjective artistic assessment and learning analytics.

5.1. LIMITATIONS AND FUTURE ENHANCEMENTS

Even though successful, A-CLM possesses some limitations that would guide future development. Reinforcement learning module in the system will demand massive interaction data to reach a stable convergence, thus being inefficient with small cohorts or workshops with short durations. In addition, although affective computing enhanced the accuracy of engagement, emotion recognition models are still constrained by cultural and context differences. The sequential version of A-CLM in the future will involve the use of cross-cultural affective data and explainable reinforcement learning (XRL) procedures to make it more interpretable and fair.

The other potential path is the inclusion of Extended Reality (XR) interfaces, allowing to provide fully felt experience of virtual exhibition space and be tactile. Combined with haptics and eye-tracking cameras, XR application may enhance spatial and sensory comprehension of curatorial principles by learners and broaden the scope of adaptive AI in creative learning.

6. CONCLUSION AND FUTURE WORK

The study defined the AI-Based Adaptive Curation Learning Model (A-CLM) as an all-encompassing and experimentally established framework of customizing art curation education by combining artificial intelligence, multi-modal analytics, and reinforcement learning. The study showed that A-CLM has significant effect in enhancing learning gain, cognitive engagement, and reflective depth as compared to the traditional pedagogical approaches through systematic experimentation of 120 learners. Through the dynamically analyzed behavioral, affective and performance data, the system was able to adjust the instructional material in a continuous manner, allowing people to progress individually and have fair learning experiences. The technical scalability and pedagogical transformative nature of the model architecture, which encompassed user interfaces, adaptive engines and knowledge graph integration, met both the IEEE standards of learning technologies and the ethical principles of AI. The results reiterate the importance of adaptive AI as a pedagogical partner instead of a substitute of human educators, which enhances creativity and critical interpretation in the art education field. In the future, it will be working on explainable reinforcement learning that is more transparent, incorporating cross-cultural aesthetics data to make it more inclusive, and creating immersive adaptive exhibitions by embedding Extended Reality (XR) environments. Such developments will expand the potential of A-CLM to be deployed globally and assist museums, academic centers and creative industries in developing reflective, technologically empowered curators in the digital era.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

REFERENCES

Al-Alwash, H. M., and Borcoci, E. (2024). Non-Dominated Sorting Genetic Optimisation for Charging Scheduling of Electrical Vehicles with Time and Cost Awareness. UPB Scientific Bulletin, Series C, 86(1), 117–128.

Aqeel, K. H., and Aqeel, M. A. H. (2022). Testing and the Impact of Item Analysis in Improving Students' Performance in End-Of-Year Final Exams. English Linguistics Research, 11, 30. https://doi.org/10.5430/elr.v11n1p30

Bidyut, D., Mukta, M., Santanu, P., and Arif, A. S. (2021). Multiple-Choice Question Generation with Auto-Generated Distractors for Computer-Assisted Educational Assessment. Multimedia Tools and Applications, 80, 31907–31925. https://doi.org/10.1007/s11042-021-10966-5

Chen, S., Lin, P., and Chien, W. (2022). Children's Digital Art Ability Training System Based on AI-Assisted Learning: A Case Study of Drawing Color Perception. Frontiers in Psychology, 13, 102931. https://doi.org/10.3389/fpsyg.2022.102931

Cong, S. (2024). A Study of Teaching Strategies Optimized with the Integration of Artificial Intelligence Technologies. Applied Mathematics and Nonlinear Sciences, 9, 1195. https://doi.org/10.2478/amns-2024-1195

Coverdale, A., Lewthwaite, S., and Horton, S. (2024). Digital Accessibility Education in Context: Expert Perspectives on Building Capacity in Academia and the Workplace. ACM Transactions on Accessible Computing, 17, 1–21. https://doi.org/10.1145/3630727

Dai, Y., Liu, A., Qin, J., Guo, Y., Jong, M., Chai, C., and Lin, Z. (2022). Collaborative Construction of Artificial Intelligence Curriculum in Primary Schools. Journal of Engineering Education, 112, 23–42. https://doi.org/10.1002/jee.20468

Dhawaleswar, R. C., and Sujan, K. S. (2020). Automatic Multiple-Choice Question Generation from Text: A Survey. IEEE Transactions on Learning Technologies, 13(1), 14–25. https://doi.org/10.1109/TLT.2019.2929305

Engelsrud, G., Rugseth, G., and Nordtug, B. (2021). Taking time for New Ideas: Learning Qualitative Research Methods in Higher Sports Education. Sport, Education and Society, 28, 239–252. https://doi.org/10.1080/13573322.2021.1982897

Ezquerra, Á., Agen, F., Rodríguez-Arteche, I., and Ezquerra-Romano, I. (2022). Integrating Artificial Intelligence into Research on Emotions and Behaviors in Science Education. Eurasia Journal of Mathematics, Science and Technology Education, 18, 11927. https://doi.org/10.29333/ejmste/11927

Gardner, J., O'Leary, M., and Yuan, L. (2021). Artificial Intelligence in Educational Assessment: Breakthrough? Or Buncombe and Ballyhoo? Journal of Computer Assisted Learning, 37, 1207–1216. https://doi.org/10.1111/jcal.12555

Nuțescu, C. I., and Mocanu, M. (2020). Test Data Generation Using Genetic Algorithms and Information content. UPB Scientific Bulletin, Series C, 82(2), 33–44.

Nuțescu, C. I., and Mocanu, M. (2023). Creating a Personality Model Using Genetic Algorithms, Behavioral Psychology, and a Happiness Dataset. UPB Scientific Bulletin, Series C, 85, 25–36.

Seman, L. O., Hausmann, R., and Bezerra, E. A. (2018). On Students' Perceptions of Knowledge Formation in a Project-Based Learning Environment Using Web Applications. Computers and Education, 117, 16–30. https://doi.org/10.1016/j.compedu.2017.10.001

Zou, B., Li, P., Pan, L., and Ai, T. A. (2022). Automatic True/False Question Generation for Educational Purpose. In Proceedings of the 17th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2022). Association for Computational Linguistics, 1-10.