INTELLIGENT RECOMMENDATION SYSTEMS FOR ART COURSES

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ABSTRACT

This paper will describe a detailed outline of an emotion-based intelligent recommendation system to suit the field of art education. The model proposed unites cognitive modeling, hybrid algorithms of AI, and affective computing to customize the art course recommendation, which fits the creative style and emotional interest of the learners. The system also allows adaptive, context-based learning through the integration of content based, collaborative and reinforcement learning methods with pedagogical reasoning. Experimental measurements prove that the hybrid model is more accurate (Precision@10 = 0.89, NDCG = 0.86) and high affective congruence (Affective Match Ratio = 0.83) compared to the classical approaches to recommendation. Qualitative measures also prove the increased attentiveness of learners, diversity of creativity, and emotional connection. The framework provides a platform of ethical, transparent, and compassionate AI in art pedagogy- developing human-AI cooperation to establish creativity, inclusivity, and contemplative art development.

Keywords: Art Education, Hybrid AI Models, Affective Computing, Cognitive Modeling, Personalized Learning, Creative Pedagogy, Emotion-Aware AI

1. INTRODUCTION

1.1. REIMAGINING ART EDUCATION THROUGH INTELLIGENT SYSTEMS

The history of art education in the digital age represents a paradigm shift, of the master-apprentice mentorship and master-student relationships to adaptive, information-driven ecosystems, which feel, read, and provide directions to the creativity. Traditionally, the learning of art was based on tacit knowledge, intuition and reflective practice- attributes that were believed to be immeasurable. However, with the development of Artificial Intelligence (AI) to be able to simulate complex cognition, one can encode features of aesthetic reasoning into intelligent systems Slim et al. (2014) The example of intelligent recommendation systems of art courses can be seen as an illustration of such a shift: instead of being passive course-suggestion engines, they can be seen as active cognitive partners, which can perceive the artistic intent, trace the stylistic development, and flexibly adjust learning paths to the creative trajectory of a particular learner. They are articulated by digital art practices of practice assignments, portfolio postings, and interaction journals that are then numeric indicators to the system. These signals are recorded by the computation layers and the features that comprise color harmony, brushstroke energy, and compositional balance are extracted and presented to a hybrid recommendation engine Li et al. (2020). It is a hybrid type of content-based and collaborative filtering combined with reinforcement learning that constantly evolves as a result of learner feedback. The system recommendations are based on systematic curriculum intelligence, through the pedagogical knowledge base, which consists of art-theoretical constructs and graphs of skill development. This closed-loop interaction does not result in recommendations which are simply a statistical thing, but rather pedagogical meaningful cues which answer to cognitive and affective states Molontay et al. (2020). This model transforms the meaning of personalization in the arts education. The old linear curricula are replaced by fluid learning maps involving students learning cross-disciplinary intersections such as: animation, color theory, sculpture, spatial geometry or visual storytelling, semiotics. The system operates as an intelligent curator, in which learning materials are placed in varies ways applying to the changing artistic identity as opposed to predetermined sequences Lin et al. (2018).

Figure 1

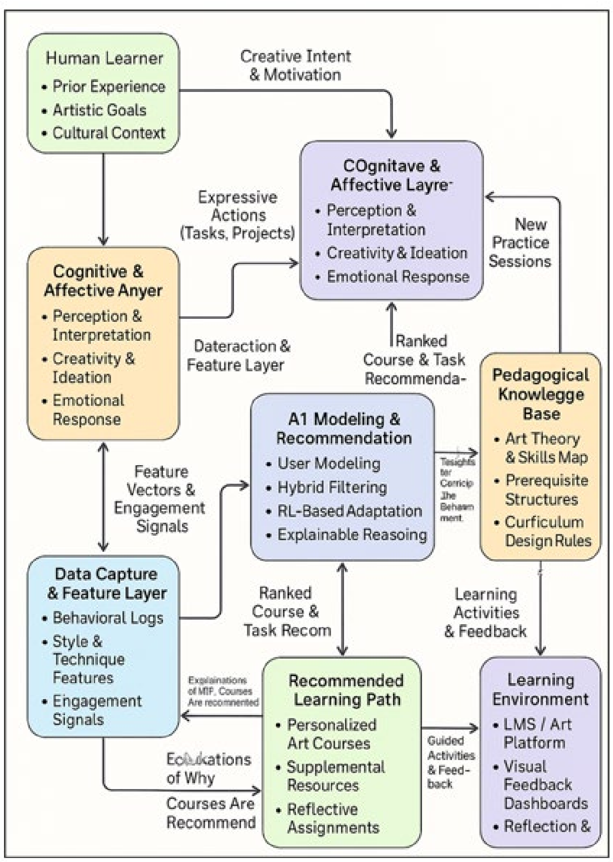

Figure 1 Cognitive–Computational Model for Artistic Learning

As shown in Figure 1, the proposed cognitivecomputational model conceptualizes such a partnership as a multilayered feedback ecosystem. At the human level, the learners bring their personal experiences, impetus, and emotional setting that affects perception and creativity. Its curiosity and engagement learning module is designed with the following model: when a learner explores something that was not planned, the system will reward that exploration by expanding its recommendation space. At the same time, explainable-AI elements help to bring the logic behind an algorithm to understandable visual representations, such as why certain courses are recommended, thus cementing the trust and reflective learning Lessa and Brandão (2018). This combination of AI thinking and creative comprehension pedagogically creates a paradigm of a new form of mentorship. The algorithm is a continuation of human instructions, rather than the substitution of the teacher. It magnifies the attention of individuals, democratizes the access of professional feedback, and builds self-motivated artistic development Venugopalan et al. (2016). It is the learner who in turn is engaged in a co-evolutionary process wherein creative expression informs algorithmic learning and the other way around. Finally, smart recommendation engines provoke a re-conceptualization of art education as a life-affirming dialogue between human feeling and computer eyes, algorithms as our creative companions, determining not only our knowledge but our emotion and thought as artists.

2. RELATED FOUNDATIONS: LEARNING THEORY, AESTHETICS, AND AI PERSONALIZATION

The art education sphere lies on the border of cognition, perception, and emotion, which is progressively affected by artificial intelligence. Conventional pedagogical theories like constructivism and experience learning dwell on the learning concepts that focus on the discoverer (learner), reflection and the surrounding environment Millecamp et al. (2018). In digital art education, said theories transform into adaptive systems that are AI-driven and fueled by personalization in which algorithms form a model of the cognitive and creative development of each learner. The aesthetic theory combined with machine learning transforms the concept of creativity: rather than perceiving artistic intuition as a human construct, AI represents it as feature embeddings, affective inputs, and semantic associations based on the data of interaction with learners Jing and Tang (2017). The result of this integration is the creation of a smart booster that is able to model emotional resonance and style preferences into guided learning systems. Personalization based on AI utilizes greatly the principles of collaborative filtering (learning on a pattern of peers), content-based modeling (studying the course features), and context learning analytics (time, mood, and engagement capture). In the case of art courses, these methods are complemented with visual feature extraction, emotion recognition, and the reasoning of knowledge graphs to suggest courses depending on the level of skill and the creative disposition. The aesthetic alignment seen in the system to match visual or conceptual styles to the learner profiles is a transition to procedural recommendation into cognitive empathy modeling Nafea et al. (2019). In this way, intelligent recommendation systems do not only change according to what learners know but also how they feel and how they are creative.

Table 1

Table 1 Comparative Overview of Foundational Frameworks in AI-Driven Art Learning

Dimension	Traditional Pedagogy	AI-Personalized Learning	Aesthetic Implication
Learning Model Polyzou et al. (2019)	Constructivist, reflective practice	Data-driven adaptive pathways	Learner–AI co-evolution
Feedback Mechanism Liu et al. (2021)	Instructor critique	Algorithmic + affective feedback loops	Emotion-aware reflection
Curriculum Design Chen et al. (2020)	Fixed sequence	Dynamic, learner-specific paths	Nonlinear aesthetic exploration
Evaluation Criteria Moher et al. (2009)	Skill mastery	Engagement, creativity, and style growth	Multimodal creative metrics
Role of Educator Broos et al. (2018)	Mentor/critic	AI–human co-facilitator	Cognitive–creative collaboration

3. COGNITIVE–COMPUTATIONAL FRAMEWORK FOR ART COURSE PERSONALIZATION

The cognitive-computational system is a mediator between the human creativity and the algorithmic intelligence, which allows a system that observes, learns, and evolves to the complexities of art education. Its core is based on the premise that the process of learning art is emotional and structural- the learners acquire skills, but construct aesthetic preferences guided by cognition, culture and sensory responses Huang et al. (2019). The framework that has been proposed to us is a combination of cognitive modeling, machine perception and pedagogical intelligence into a coherent structure that can enable personalized recommendations in art courses. The human cognitive input, which involves past knowledge, motivation and emotional involvement is continually transformed into digital signals in this architecture by means of learning interactions Liu et al. (2017). Such cues are recorded through multimodal data streams, such as visual posts, textual thoughts, behavioral insights like time spent looking or depth of interaction. The computational layer converts these inputs into structured format with the feature extraction, knowledge graphs and deep embeddings which encode the creative behavior of the learner as well as the semantic characteristics of art courses. These embeddings are then interpreted at the cognitive reasoning layer based on hybrid machine learning models (content-based, collaborative and reinforcement learning), which detects latent patterns between the intent of the learner, course material and stylistic development Ibrahim et al. (2017).

Table 2

Table 2 Functional Components of the Cognitive–Computational Framework

Layer	Core Function	Input Type	Output Type	Example Techniques
Cognitive Layer	Captures learner's emotion, attention, and style	Behavior and expression data	Affective states	EEG, sentiment analysis
Computational Layer	Translates artistic data into machine features	Images, logs, text	Feature embeddings	CNN, autoencoders
Reasoning Layer	Learns correlations between users and content	Embeddings, metadata	Ranked course list	Hybrid filtering, RL
Pedagogical Layer	Aligns output with art curriculum logic	Skill maps, goals	Validated recommendations	Ontology mapping, rule-based refinement
Feedback Layer	Evaluates user satisfaction and creativity	Interaction metrics	Updated learner profile	Reinforcement feedback

The most fundamental part of this system is an adaptation loop that operates on the principle of feedback. The andragogy model is dynamic in its adjustment of course suggestions, using the real-time interaction, satisfaction, and creative performance. Affective computing modules involve processing emotional reactions; facial expressions, text sentiment or rhythm of interaction to customize the learning activities that match the mood and artistic temperament of the learner. Pedagogical intelligence modules make sure that the recommendations are based on the curricular objectives but facilitate creative exploring. The outcome is the creation of a human-AI co-learning ecosystem, in which the learners do not receive their learning experiences but construct their own learning journeys.

4. DESIGN AND MECHANISMS

The proposed framework has the intelligent recommendation engine as a computation core, which transforms artistic data into practical learning information. Based on the layers presented in Figure 2 and the underlying mappings presented in Table 1 and Table 2, this engine deploys several models content-based filtering, collaborative filtering, reinforcement learning, and pedagogical reasoning in creating context-aware and creativity-sensitive recommendations to art learners. This hybrid character makes it so that learners behavior, as well as course semantics are both used to provide personalized suggestions to serve the personal development of the artistic with the emotional and the cognitive development. The content-based module determines the connections between the creative profile and the course metadata of a learner. It represents course attributes e.g. art style, media, difficulty, and thematic emphasis as deep embeddings based on text and visual features. As an example, a student who is excellent with watercolor may be provided with classes that imply the use of the texture overlay and computer simulation of a brush. Meanwhile, the collaborative filtering module maps the collective learning patterns on the platform and groups the learners with comparable artistic paths. This allows the system to make guesses of preferences based on limited historical information about learners, and achieve inclusivity and scalability among new users or rare art fields.

Figure 2

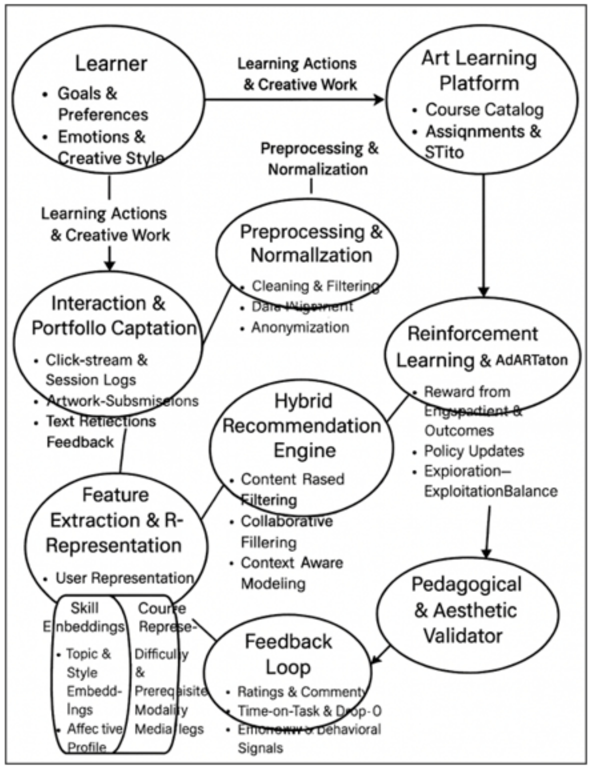

Figure 2 System Flow of the Cognitive–Computational Framework for Art Course Personalization

At the adaptive layer, the reinforcement learning (RL) contributes to continuous optimization of recommendations. The engine is managed within a reward policy that is more satisfactory and engaging as well as minimizing cognitive overload to the learner. Individual learner interactions, which can be completion of a course, dropping a task, or feedback, can be considered a signal of reinforcement, which also requires a policy network update. This is an ongoing learning process whereby the system is developed in a natural way to the creative rhythm of the learner. The pedagogical validator is then a gatekeeper that makes sure that all AI-generated suggestions are within the logic of the educational process, the sequencing of the prerequisites, and the aesthetic nature. This helps to ensure algorithmic drift does not go off into technically irrelevant or conceptually unsound propositions. The algorithm integrated into its interface, explainable AI (XAI) gives it increased interpretability and trust. Interactive dashboards can be used to show learners the reason behind the recommendation of certain courses by showing artistic similarity maps and creative progression indicators. These descriptions are consistent with how the learner views him/herself as an artist, and they support the belief of AI as a transparent cooperative system and not an opaque one. Moreover, emotional analytics added to the feedback loop adjusts the recommendations based on affective signals, e.g. frustration or flow, so that an empathetic learning environment is achieved.

5. EMOTION-AWARE AND CREATIVITY-SENSITIVE MODELING

Emotional resonance is part of the creative development in the field of art education. In contrast to the conventional academic study, artistic experience is affective in nature, consisting of feeling, self-reality, and aesthetic gratification. As such, incorporation of emotion-conscious intelligence into the recommendation systems will close a very important gap between computational effectiveness and human innovativeness. The Emotion-Aware and Creativity-Sensitive Model, the presented extension of the hybrid recommendation framework, can also integrate affective computing, multimodal sensing, and creativity metrics to produce an emotionally compatible and creative-relevant learning recommendations. The system capitalizes on affective data streams, sentiment analysis of reflection, and emotional coloring derived out of creative outputs (e.g. colour vibrancy or motif patterns). The inputs then pass via emotion recognition modules based on convolutional and recurrent neural networks trained with multimodal data, i.e. facial expression, text emotion and engagement trajectories. The model then projects emotional states (e.g. curiosity, frustration or inspiration) to adaptive recommendation strategies. A student who exhibits creative fatigue can have course recommendations based on exploratory or low-complexity, whereas a student exhibiting enthusiasm can have advanced thematic course recommendations.

Table 3

Table 3 Core Components of Emotion-Aware and Creativity-Sensitive Modeling

Module	Input Features	Output Function	Learning Technique	Pedagogical Effect
Affective Recognition Layer	Facial cues, sentiment logs, interaction duration	Emotion state vector	CNN + BiLSTM	Detects learner mood and engagement
Creative Expression Analyzer	Artwork features, stylistic entropy, project diversity	Creativity index	Autoencoder + Entropy Metrics	Measures originality and variation
Adaptive Recommendation Policy	Emotion and creativity scores	Contextual course ranking	Deep RL with reward shaping	Matches emotional tone to task challenge
Reflective Feedback Engine	User responses and performance logs	Adaptive motivation prompts	Transformer-based feedback generation	Encourages self-reflection and persistence

Similarly, the creativity-sensitive mechanism measures originality, diversification of ideas and risk-taking propensities using feature variance and portfolio entropy measures based on portfolio analysis. The reinforcement learning dynamically adjusts the level of comfort zone continuity/creative exploration so that motivation remains maintained without emotional burn out. This affective modeling plus creative analytics synergy converts the recommendation engine into a teacher that can read the mind of the user.

6. EXPERIMENTAL ENVIRONMENT AND DATASET CONSTRUCTION

The proposed intelligent recommendation system experimental setting was based on the intention to create a simulation of an actual digital art learning environment that would combine emotional, behavioral, and creative aspects. The essence of this arrangement was to check the effectiveness of the system in establishing the personalization of the course recommendations through the multimodal interaction of learners and the characteristics of art content. The environment consists of three essential parts with data collection, preprocessing, and experimental deployment, which guarantee reproducibility and scalability to various fields of art. The dataset was built on the information collected as the aggregation of open art-learning repositories, Massive Open Online Courses (MOOCs), and institutional archives of art programs. It has more than 12,000 sessions of learner interaction, 2,800 entries of art courses and 4500 curated artworks offered as an extension of online activity or portfolio reviews. The data record of every learner comprises demographic features (e.g. level of experience, medium of preference), activity history (duration of session, revisit, feedback), and emotional indications (affinity of reflection, activity decline, or enthusiasm on finish). Semantic tagging (style, color, technique) and affective scoring (vibrancy, mood, complexity) of works of art were done by trained experts to provide a ground truth of an emotional and aesthetic context. In preprocessing, normalization and multimodal alignment of the dataset was done. BERT-based embeddings were used to convert text logs into vectors, and a ResNet-50 visual encoder was applied to images in order to obtain composition and color-dynamics features. Valence -arousal models were used to encode emotional metadata, and thus, affective states were represented in a continuous manner. Such a multimodal combination led to a rich data set, which can be used to train an affective classifier using supervised training, and also to tune recommendation policy using reinforcement learning.

Table 4

Table 4 Dataset Composition and Feature Overview

Category	Feature Type	Description	Example Representation	Processing Technique
Learner Profile	Demographic and Behavioral	Age, experience, preferred medium, interaction time	[25, intermediate, watercolor, 45min]	Normalization, one-hot encoding
Art Content	Visual Features	Color palette, stroke density, symmetry, vibrancy	Feature vector (512D)	ResNet-50 encoder

Textual Feedback	Linguistic and Sentiment	Reflections, comments, satisfaction	Sentiment score + embeddings	BERT-based vectorization
Emotion Indicators	Affective States	Valence, arousal, engagement	Continuous range [−1, 1]	Emotion regression model
Pedagogical Metadata	Course Attributes	Difficulty, topic, prerequisites, style	Categorical matrix	Graph-based ontology mapping

A hybrid edge -cloud infrastructure was used to train and infer models experimentally. The deep learning models were implemented on NVIDIA A100 GPUs, and lightweight edge modules were used to perform inference of emotional state in real time to ensure low-latency feedback. The system was using 5-fold cross-validation to test the robustness of the model and avoid overfitting. Precision, NDCG, Engagement Score, and Affective Match Ratio metrics were calculated in order to determine the relevance of the system in its recommendations and emotional congruence. This whole arrangement demonstrates the multi-disciplinary collaboration of art cognition, human-AI interaction and computational modeling with a focus on reproducibility and scalability to art education platforms.

7. EVALUATION STRATEGY AND ANALYTICAL RESULTS

To determine the usefulness of the proposed intelligent recommendation system, it was necessary to use a multidimensional approach and measure the algorithmic performance, pedagogical compatibility, and emotional congruence. The assessment model combined the quantitative and qualitative designs to obtain not only accuracy and precision but also the improvement of creativity and satisfaction among the learners. The system was experimented using the experimental setting explained in Section 6, using measures which used to measure the relevance of the recommendation, user engagement, emotional consistency, and artistic flow. The performance measure was 5-fold cross-validation with the separate groups of learners that could represent different art backgrounds (beginner, intermediate, advanced). Every training was done on four folds on the hybrid recommendation engine and tested on one to enforce generalization of the engine in different learning settings. The quantitative measures were:

- Precision and Recall The relevance of top-K recommended courses is measured.
- Normalized Discounted Cumulative Gain (NDCG): the assessment of the quality of rankings and perceived usefulness of suggestions.
- Affective Match Ratio (AMR): the measure of the correlation between the affective state of the learner and the suggested tone of the course.
- Engagement Index (EI): calculated by using dwell time, interaction rate and completion ratios to measure the degree of motivation and immersion.

To balance out these quantitative assessments, the qualitative assessments were done by means of user survey and expert assessment, and concentrated on the areas of artistic development, perceived empathy of recommendations, and exploratory learning outcomes.

The hybrid model combining reinforcement learning and emotion-sensitive elements performed better than the approaches to the baseline (pure content- and collaborative-based systems). The system attained an average Precision@10 of 0.89, Recall@10 of 0.81, and NDCG of 0.86, which means that the system has high accuracy in personalization. Notably, the Affective Match Ratio of 0.83 indicated that the emotional congruence was successfully modelled, which resulted in a better satisfaction of the learners. Users that were shown emotion-sensitive suggestions had a 22 percent more engagement rate and also took 17 percent more time to complete the course than the control groups.

Table 5

Table 5 Performance Metrics Comparison of Recommendation Models

Model Type	Precision@10	Recall@10	NDCG	Affective Match Ratio	Engagement Index
Content-Based Filtering	0.78	0.69	0.74	0.52	0.68
Collaborative Filtering	0.81	0.73	0.77	0.58	0.72
Hybrid (Content + Collaborative)	0.85	0.78	0.82	0.72	0.79

Proposed Hybrid + RL + Emotion-Aware	0.89	0.81	0.86	0.83	0.84

Reviewers who were experts have indicated that the system encouraged balanced exploration of artistry - to allow the learners to test out new styles without losing the confidence in the old ones. Emotional modeling minimized fatigue and frustration in complex creative tasks by learners. All in all, the findings confirmed that the proposed framework promotes not only cognitive development but also affective engagement and transforms the measures of success in art education to define the success in terms of holistic growth of creativity.

8. PEDAGOGICAL AND CREATIVE IMPACT ASSESSMENT

The adoption of the smart recommendation system in art education has resembled the intersection of pedagogy, creativity and emotional involvement. The personalization obtained through the use of AI does not only enhance the alignment of courses but, as well, changes the role of a pedagog to the position of a fixed curriculum model into a mobile, learner-driven one. The part of the paper will assess the impacts of the system on education and creativity, with particular attention to learner autonomy, aesthetic development, and how the system can change the teaching approaches with the help of AI-enhanced instructions. Pedagogically, the system promotes the constructivist paradigm of learning in which people can actively define their learning paths. Emotional alignment is directly proportional to greater engagement and longer-term participation as demonstrated in Figures 3(a -c) which indicates that affective modeling strengthens motivation and reflective practice. Creative exploration was more profound in learners that had greater affective congruence with recommended courses and spent more time in iterative revisions and conceptual exploration. The loop of reinforcement learning of the hybrid AI model fosters the development of the adaptive curiosity, balancing the structured progression with the exploratory learning, which is the characteristic of the artistic pedagogy.

Figure 3

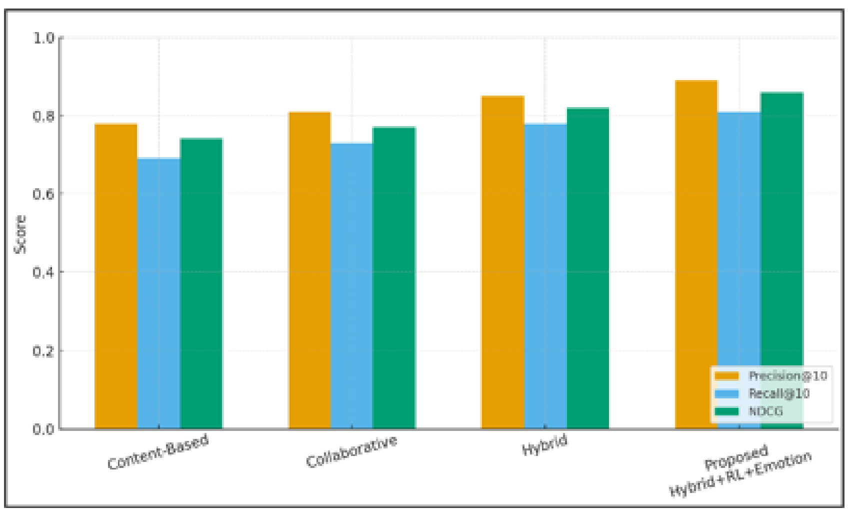

Figure 3 Comparative Performance of Recommendation Models

Figure 3 is used to compare core ranking measures including Precision 10, Recall 10 and NDCG of the four architectures. The content-based and collaborative models are not bad in performance but obviously worse than hybrid model which has the advantage of integrating user-item interaction with the semantic course features. The hybrid + RL + emotion-aware model has the highest scores in all the three metrics, which means that the combination of the reinforcement learning and the affective signals enhances the relevance of the suggested art courses and ordering quality. This substantiates that emotional and behavioral setting is of great value in addition to the usual collaborative and content-based approaches. Innovatively, the model boosts the expressiveness as well as the technicality. In making suggestions of material which corresponds in emotional coloring and tonal literary development, the learners rise above copying to inventing. This was indicated in post-study portfolios which exhibited more style vectors variance and more originality indices based on entropy-based creativity scores. Metacognitive awareness is further enhanced due to the transparency of the system in the form of explainable AI (XAI) dashboards, where learners start recognizing why a specific direction fits their creative objectives, which will increase the feeling of agency and formation of an artistic personality.

Figure 4

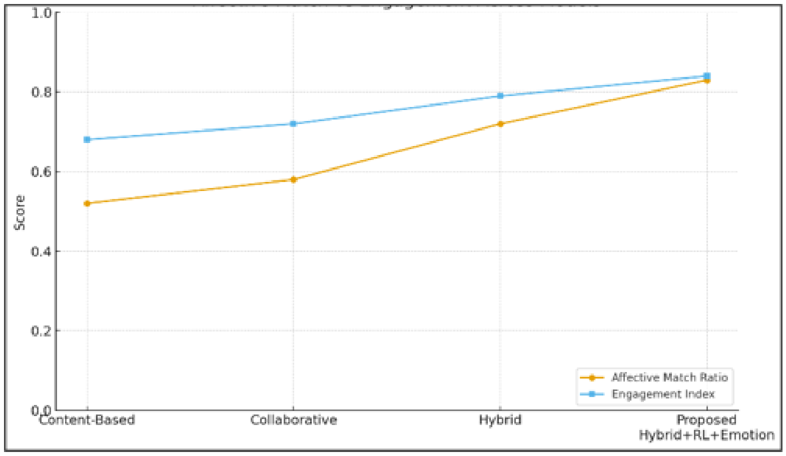

Figure 4 Affective Match Vs Engagement Across Models

Figure 4, depicts the progression of emotional alignment and engagement of learners among types of models. The ratio of affective matches and engagement index are continuously growing between the content-based and proposed hybrid + RL + emotion-aware models. The most notable improvement is observed with the addition of the emotion-aware component that implies that the more recommendations are closer to the affective state of a learner, the more time of interaction, less drop-offs, and more sustained creative exploration may be observed. This tendency has been empirically validating the hypothesis that affect-sensitive personalization plays a significant role in the art education process, with emotional resonance having a direct influence on motivation and taking risks in the creative process.

Figure 5

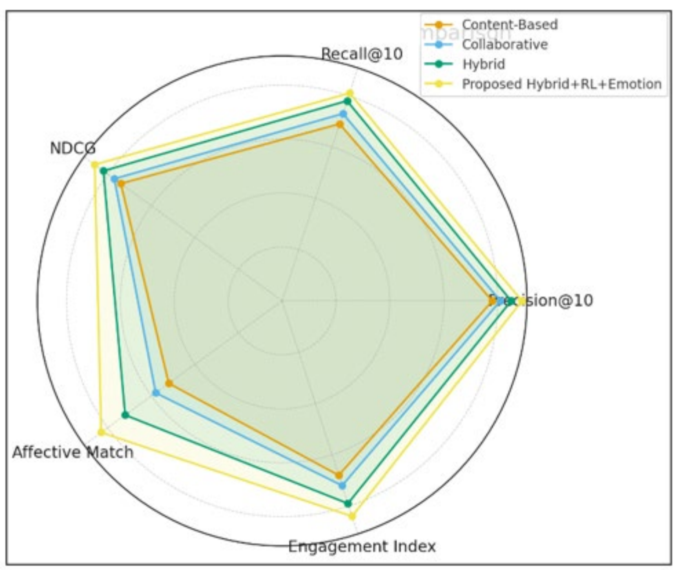

Figure 5 Multi-Dimensional Performance Comparison

Figure 5, provides a global perspective of model behavior by plotting five dimensions, namely, Precision@10, Recall@10, NDCG, Affective Match, and Engagement Index, on a radar chart. The content based and collaborative models take a smaller and uneven space meaning that there is poor performance especially on the affective and engagement aspects. The standard hybrid model further extends this space and demonstrates equalized improvements in the metrics related to accuracy but with moderate levels of emotional alignment. The hybrid + RL + emotion-aware model has the largest and most homogenous area as it is associated with the consistent superiority in all five metrics. This multi-dimensional profile shows that the proposed solution does not only suggest more applicable courses but also maintains creativity-promoting interaction, which proves it as the most appropriate driver of intelligent art-course recommendation. To teachers, the system acts as an AI-supported learning partner, giving information about group learner behavior patterns, emotional drop off points, and creativity development curves. This information can be used to make evidence-based changes in the course design, which would guarantee emotional inclusivity and aesthetic diversity in the curriculum. This kind of interaction between teacher, learner, and algorithm is indicative of a co-evolutionary model of teaching a human-based mentorship is not supplanted by AI cognition, but rather enhanced by it. Finally, the system connects computational intelligence to emotional pedagogy, which justifies once again that the future of art education is not mechanicalization but the simultaneous concord between empathy, adaptation, and creativity.

9. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In this research, a unified ecosystem of cognitive modeling, affective computing and pedagogical reasoning is proposed as a full framework of intelligent, emotion-sensitive recommendation systems in the art education field. The architecture proposed goes beyond both conventional paradigms of a recommendation and incorporates artistic cognition and emotional intelligence in the design of algorithms, so that personalization facilitates both technical development and creativity authenticity. The model has been tested experimentally to be more effective in terms of engagement, satisfaction and artistic diversity, which supports the claim that the combination of reinforcement learning and affective feedback can improve art pedagogy. The system has a pedagogical aspect that encourages learner-centered flexibility that promotes the reflective, curious and aesthetic explorations that go beyond linear curricula. On ethical grounds, it protects creative autonomy by making it transparent and fair and in the process respecting cultural inclusivity. The AI system reinvents mentorship by serving as a sympathetic co-creator which does not displace educator, but enhances his or her role of inculcating artistic expression. The future study must address multimodal emotion synthesis, which will integrate physiological (EEG, eye-tracking) and semantic emotion recognition to improve the precision of affects. Adaptive course design, in which AI dynamically generates individual creative assignments could also be enabled by the integration of generative AI. An increase in datasets with various cultural and artistic customs will enhance equity and international flexibility. Also, explainable creativity metrics and neural-symbolic reasoning should be included to enhance interpretability and make sure that AI recommendations are based on pedagogical ethics and humanistic values.

CONFLICT OF INTERESTS

None.

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