HOW GENERATIVE AI ENHANCES SMART CLASSROOMS AND SUPPORTS THINKING DEVELOPMENT

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As educational digitalization accelerates, the need for intelligent technologies in teaching and learning is becoming increasingly pressing. This study introduces a deep hybrid recommendation framework, VAE-GAN-DCR, built on variational autoencoders (VAE) and generative adversarial networks (GAN), and examines how generative AI can contribute to smart-classroom practice. Methodologically, the model integrates the VAE decoder with the GAN generator, extends standard VAE design by incorporating item-feature–dependent prior distributions, and reduces reconstruction error by leveraging feature-transfer signals from the GAN discriminator to improve educational resource recommendation accuracy. In addition, teaching outcomes at Zhanjiang Early Childhood Teacher Training College are assessed using the Williams Creative Tendency Measurement Scale. Experimental results show that VAE-GAN-DCR achieves strong performance across three datasets; on MovieLens-1M, Recall@20 increases by 12.15% and NDCG@100 by 12.94%. Classroom application results further indicate that the experimental group outperforms the control group in creative-thinking activities and creative tendency, with the overall creative tendency score reaching 2.61. The findings suggest that generative AI can both enhance the precision of educational resource recommendations and foster students' creativity, providing robust support for smart-classroom development.

Index Terms — generative artificial intelligence, smart classroom, variable score autoencoder, generative adversarial network, educational resource recommendation, creative thinking activity

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INTRODUCTION

Artificial intelligence (AI) has advanced rapidly in recent years and is increasingly recognized for its transformative impact across a wide range of domains. Within this broader landscape, generative AI has emerged as a particularly influential direction. Beyond its well-known applications in creative industries such as art and literature, generative AI is now demonstrating strong potential to reshape educational practices and learning environments [1, 2]. In general, generative AI refers to machine-learning-driven techniques that learn patterns from large-scale data and then produce novel outputs, including images, music, and text [3, 4]. Existing generative approaches are commonly grouped into rule-based methods and neural-network-based methods. Rule-based systems depend on hand-crafted generation rules, whereas neural methods learn generation mechanisms directly from data through model training; among these, generative adversarial networks (GANs) are among the most widely adopted frameworks [5, 6, 7].

In education, the value of generative AI is most prominently reflected in two directions: individualized instruction and virtual experimentation [8]. For individualized instruction, generative models can create learning materials that align with a learner's interests, abilities, and preferred learning styles [9]. By mining students' learning behaviors and feedback signals, such systems can adapt content difficulty, recommend suitable resources, and design learning trajectories that better match individual needs [10, 11]. This adaptive mode of instruction has the potential to improve learning outcomes, enhance motivation, and alleviate learning-related stress [12]. In parallel, when laboratory resources are limited, generative AI can support teaching through simulation by constructing virtual experimental scenarios [13, 14]. By synthesizing experimental settings under diverse conditions in accordance with physical principles and empirical data, generative systems can offer students richer opportunities for practice and observation, thereby strengthening understanding of experimental procedures and underlying scientific concepts [15, 16, 17].

Motivated by these opportunities, this study presents a smart classroom framework built upon a VAE–GAN deep composite recommendation (VAE–GAN–DCR) model. The proposed approach integrates the representation and generation capability of a variational autoencoder (VAE) with the adversarial optimization mechanism of a GAN to improve educational resource recommendation. The work is organized at two complementary levels. At the technical level, the VAE–GAN–DCR model is developed by enhancing the conventional VAE structure through the introduction of an item-dependent prior distribution and by leveraging a GAN discriminator to refine reconstruction quality, enabling more accurate modeling and recommendation of educational resources. At the application level, the framework is validated in educational practice through comparative experiments, examining how generative AI–assisted smart classrooms influence students' creative thinking ability. The findings provide empirical evidence to support the broader deployment and adoption of generative AI technologies in smart classroom settings.

METHODOLOGY

Deep Learning–Based Recommendation Techniques

Variational Autoencoders

Autoencoders are neural network models designed to compress input data into a lower-dimensional representation and subsequently reconstruct the original input from this compressed form. They typically consist of two main components: an encoder, which transforms the input into a latent representation, and a decoder, which attempts to reconstruct the original data from this latent code.

While conventional autoencoders can accurately reconstruct input data, overly precise reconstruction may result in trivial identity mappings, limiting the model's ability to learn meaningful representations. To avoid this issue, additional constraints are imposed on the latent space so that the learned representation exhibits desirable statistical properties.

The variational autoencoder (VAE) extends this framework by introducing a probabilistic formulation grounded in variational Bayesian inference. Instead of learning deterministic latent representations, VAEs approximate the posterior distribution of latent variables using tractable distributions. This formulation allows efficient optimization through stochastic gradient methods and enables principled generative modeling.

Earlier approaches typically employed mean-field approximations for posterior inference. However, in the VAE framework, inference is performed by maximizing a variational lower bound on the data log-likelihood. The stochastic gradient variational Bayes (SGVB) estimator further enables efficient learning by approximating posterior expectations using stochastic optimization.

Let $q_\phi(z|x)$ denote the encoder, which approximates the posterior of the latent variable z given input x, and let $p_\theta(x|z)$ denote the decoder, which reconstructs the input from z. The encoding and decoding processes can be expressed as:

$$z \sim q_\phi(z|x), \quad x' \sim p_\theta(x|z). \tag{1}$$

The latent variable z is sampled from a Gaussian distribution parameterized by the encoder output, and the decoder generates new samples with similar statistical properties.

Generative Adversarial Networks

Generative Adversarial Networks (GANs) were introduced to generate new data samples that resemble the original training distribution [18, 19]. Unlike traditional generative models that rely on sampling existing examples, GANs learn a direct mapping from random noise z to the data space x. Typically, the noise vector follows a Gaussian distribution.

A GAN consists of two competing neural networks: a generator $G(z;\theta)$ that produces synthetic samples, and a discriminator $D(x;\gamma)$ that attempts to distinguish real data from generated data. The generator aims to deceive the discriminator, while the discriminator strives to correctly classify real and fake samples.

Training proceeds in two alternating steps. First, the generator is optimized to maximize the probability that its generated samples are classified as real:

$$\max_G D(G(z)). \tag{2}$$

Second, the discriminator is trained to correctly distinguish real samples from generated ones:

$$\max_D \log D(x) + \log(1 - D(G(z))). \tag{3}$$

This adversarial process is formulated as the following minimax objective:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x \sim p_{\text{data}}}[\log D(x)] + \mathbb{E}_{z \sim p(z)}[\log(1 - D(G(z)))]. \tag{4}$$

The optimal discriminator satisfies:

$$D^*(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_g(x)}, \tag{5}$$

where $p_g(x)$ denotes the generator distribution. The generator reaches its optimum when $p_g(x) = p_{\text{data}}(x)$.

VAE–GAN Based Educational Resource Recommendation Model

Model Framework

This study proposes a hybrid deep recommendation architecture that integrates a variational autoencoder with a generative adversarial network, referred to as the VAE–GAN–DCR model. The core idea is to combine the decoding process of the VAE with the generator of the GAN to exploit the complementary strengths of both models.

Let $u \in U = \{1,\ldots,m\}$ represent the user set and $v \in V = \{1,\ldots,n\}$ represent the item set. The observed user–item rating matrix is denoted by $R \in \mathbb{R}^{m\times n}$. Each user u corresponds to a row vector $\mathbf{r}_u \in \mathbb{R}^n$, representing ratings across all items, while each item v corresponds to a column vector $\mathbf{r}_v \in \mathbb{R}^m$, representing ratings from all users.

VAE Component

The VAE consists of an encoder and a decoder parameterized by λ and τ, respectively. The encoder maps the input $\mathbf{r}_v$ to a latent variable z_v, and the decoder reconstructs $\mathbf{r}_v$ from z_v:

$$z_v \sim q_\lambda(z_v|\mathbf{r}_v), \quad \mathbf{r}'_v \sim p_\tau(\mathbf{r}_v|z_v). \tag{6}$$

Unlike standard VAEs that assume a zero-mean Gaussian prior, this work introduces an item-dependent prior:

$$z_v \sim \mathcal{N}(\mathbf{y}_v, \mathbf{S}_v), \tag{7}$$

where $\mathbf{y}_v$ and $\mathbf{S}_v$ denote the mean vector and covariance matrix derived from auxiliary item features such as textual and multimedia attributes.

The decoder then maps the latent representation into a multinomial distribution over users:

$$\pi(z_v) \propto \exp(f_\tau(z_v)), \tag{8}$$

where $f_\tau(\cdot)$ is a nonlinear transformation.

The observed rating vector $\mathbf{r}_v$ is sampled as:

$$\mathbf{r}_v \sim \text{Multinomial}(N_v, \pi(z_v)). \tag{9}$$

GAN Integration

The GAN module introduces a discriminator that distinguishes between real and reconstructed rating data. Let $D_\gamma(\mathbf{r}_v) \in [0,1]$ denote the probability that $\mathbf{r}_v$ is real. The GAN loss is:

$$\mathscr{L}_{\text{GAN}} = \log D_\gamma(\mathbf{r}_v) + \log(1 - D_\gamma(p_\tau(\mathbf{r}_v|z_v))). \tag{10}$$

Instead of relying solely on pixel-level reconstruction errors, the discriminator's hidden representations are used to define a perceptual loss, which replaces the standard VAE reconstruction error.

The resulting objective function becomes:

$$\mathscr{L} = \mathbb{E}_{q_\lambda(z_v|\mathbf{r}_v)}[\log p_\tau(D^l(\mathbf{r}_v)|z_v)] - \mathrm{KL}(q_\lambda(z_v|\mathbf{r}_v)||p(z_v|\mathbf{y}_v,\mathbf{S}_v)). \tag{11}$$

The total training objective is:

$$\mathscr{L}_{\text{total}} = \mathscr{L}_{\text{GAN}} + \mathscr{L}. \tag{12}$$

Training Strategy

During parameter updates, the decoder receives gradients from both the VAE reconstruction loss and the GAN adversarial loss. A weighting parameter θ is introduced to balance these two components:

$$\tau \leftarrow \tau - \nabla_\tau(\theta\mathscr{L} + \mathscr{L}_{\text{GAN}}). \tag{13}$$

This joint optimization ensures that the decoder not only reconstructs user preferences accurately but also produces realistic samples that are indistinguishable from real data.

RESULTS AND DISCUSSION

Model Performance Evaluation

Dataset Preprocessing

For textual data representation, the Doc2Vec model was employed to learn semantic embeddings. To reduce noise and sparsity, users with fewer than five recorded interactions were removed from the dataset. The original ratings ranged from 0 to 5 and were binarized to reflect user preference more clearly. Specifically, ratings higher than 3.5 were mapped to 1, indicating user interest, whereas ratings lower than 3.5 were mapped to 0, representing disinterest or neutrality.

Evaluation Metrics

The proposed D-VAE-GAN recommendation framework focuses on top-K recommendation performance. Therefore, two widely used ranking-based metrics, Recall@K and NDCG@K, were adopted for evaluation.

Let $Te(u)$ denote the set of items that user u has interacted with in the test set, and $L(u)$ denote the recommendation list generated by the model. Recall is defined as:

$$\text{Recall} = \frac{\sum_{u\in U}|L(u)\cap Te(u)|}{\sum_{u\in U}|Te(u)|}. \tag{14}$$

Recall measures the proportion of relevant items that are successfully retrieved by the recommendation system. Higher recall values indicate stronger recommendation capability.

Normalized Discounted Cumulative Gain (NDCG) emphasizes the ranking order of recommended items and is defined as:

$$\text{NDCG} = \frac{1}{N} \sum_{u \in U} \frac{1}{\log_2(p_u + 1)}, \tag{15}$$

where p_u is the rank position of the relevant item for user u, and N denotes the total number of users. A higher NDCG value indicates better ranking quality.

Baseline Models for Comparison

To validate the effectiveness of the proposed method, the following baseline algorithms were used:

- NMF: A linear latent factor model trained using alternating least squares.
- NCF: A nonlinear collaborative filtering model based on deep neural networks.
- ReDa: A dual-autoencoder framework for learning user and item representations.
- CVAE: A Bayesian deep model based on variational inference.
- TrustSVD: A trust-aware SVD model incorporating both explicit and implicit feedback.

Training Stability and Convergence

The datasets were split into five folds, with four used for training and one for validation. The latent dimension was set to 500, and the Adam optimizer was applied. Both ReLU and Tanh activation functions were tested, and NDCG@100 was used as the primary evaluation metric.

To determine the optimal number of training epochs, experiments were conducted under different sparsity levels. As shown in Figure 1, RMSE decreases steadily with more training iterations and stabilizes after approximately 170 epochs. Hence, the number of training epochs was set to 170 for all subsequent experiments.

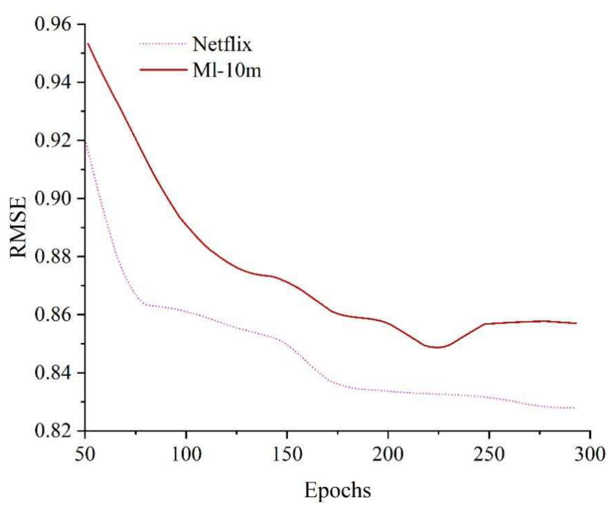

Figure 1: RMSE and the number of training times

Top-N Recommendation Performance

To examine the influence of recommendation list length on performance, Recall was evaluated at intervals of 10. The results show that Recall consistently increases with longer recommendation lists and stabilizes after $N = 40$, indicating a trade-off between list length and accuracy.

Performance Comparison

Table 1 presents the performance comparison on the MovieLens-1M dataset.

Table 1: Performance comparison on MovieLens-1M

Model	Recall@20	Recall@50	NDCG@100
NMF	0.24925	0.32914	0.30826
NCF	0.26751	0.39235	0.37291
ReDa	0.33013	0.43473	0.44513
CVAE	0.34292	0.43794	0.41397
TrustSVD	0.35083	0.45916	0.45834
VAE-GAN-DCR	0.37835	0.47197	0.47151

The proposed method achieves an average improvement of 12.15% in Recall@20, 6.11% in Recall@50, and 12.94% in NDCG@100.

Table 2: Performance comparison on MovieLens-10M

Model	Recall@20	Recall@50	NDCG@100
NMF	0.31646	0.35793	0.30571
NCF	0.35297	0.41943	0.38459
ReDa	0.36344	0.43273	0.42521
CVAE	0.38202	0.40641	0.40254
TrustSVD	0.39424	0.43782	0.44941
VAE-GAN-DCR	0.41032	0.45971	0.44637

Table 3: Performance comparison on Netflix dataset

Model	Recall@20	Recall@50	NDCG@100
NMF	0.34021	0.42735	0.37292
NCF	0.36537	0.45506	0.42016
ReDa	0.36929	0.46563	0.43683
CVAE	0.37423	0.47679	0.44874
TrustSVD	0.38137	0.47468	0.45686
VAE-GAN-DCR	0.38821	0.48893	0.47688

Educational Impact of Generative AI–Driven Smart Classrooms

Experimental Design

To investigate the pedagogical effectiveness of generative AI in smart classroom environments, a quasi-experimental study was conducted at Zhanjiang Preschool Normal College. Students of different majors and academic years, all taught by the same instructor during the same semester, were divided into two groups: an experimental group (Group A) and a control group (Group B). The average participant age was 21 years.

Group A followed a *Robotics* course, which emphasized collaborative learning through the integration of development boards, programming, and 3D printing. Group B studied *Creative Programming*, which focused on individual-based learning using the Scratch platform for tasks such as game development, motion drawing, and character modeling.

Experimental Methodology

A pre-test and post-test questionnaire-based design was employed using the Williams Creative Tendency Scale. This scale evaluates creativity across four dimensions: adventurousness, curiosity, imagination, and challenge. Each item is rated on a three-point Likert scale: 1 (not at all), 2 (partially), and 3 (completely). Higher total scores correspond to stronger creative tendencies.

To minimize confounding variables, both groups were taught by the same instructor, used identical evaluation instruments, followed the same curriculum schedule, and were drawn from similar academic backgrounds.

Homogeneity Test

Table 4 presents the independent samples t-test results of the pre-test scores, confirming that no statistically significant differences existed between the two groups prior to intervention.

Table 4: Pre-test Homogeneity Analysis

Variable	Group	Mean	Std. Dev.	t	p
Creative Thinking	Exp.	14.39	2.02	-1.04	0.319
	Ctrl.	14.89	2.22		
Fluency	Exp.	12.43	0.91	0.61	0.568
	Ctrl.	12.24	1.72		
Openness	Exp.	24.64	4.17	-0.79	0.457
	Ctrl.	25.44	4.46		
Originality	Exp.	13.52	4.26	-0.51	0.629
	Ctrl.	14.02	4.02		

Post-Test Analysis of Creative Thinking

Table 5 summarizes the post-test performance. Significant improvements were observed in the experimental group across several dimensions.

Table 5: Post-Test Creative Thinking Comparison

Variable	Group	Mean	Std. Dev.	*t*	*p*
Creative Thinking	Exp.	14.96	2.64	2.45	0.021
	Ctrl.	13.35	3.06		
Fluency	Exp.	13.18	1.20	2.37	0.022
	Ctrl.	12.05	2.69		
Originality	Exp.	13.97	4.51	2.11	0.045
	Ctrl.	11.89	3.82		
Precision	Exp.	10.45	5.50	2.15	0.042
	Ctrl.	8.01	3.91		

The results indicate that the generative AI–supported teaching approach significantly enhanced students' creative thinking, particularly in fluency, originality, and precision.

Creative Tendency Analysis

Table 6 reports the changes in creative tendencies between the two groups.

Table 6: Creative Tendency Comparison

Variable	Group	Mean	Std. Dev.	*t*	*p*
Overall Tendency	Exp.	2.61	0.43	3.35	0.003
	Ctrl.	2.33	0.39		
Adventurousness	Exp.	2.77	0.54	4.73	0.001
	Ctrl.	2.28	0.44		
Imagination	Exp.	2.72	0.53	4.85	0.000
	Ctrl.	2.25	0.39		

These findings suggest that generative AI–assisted learning environments promote stronger creative tendencies, particularly in adventurousness and imagination.

CONCLUSION

This study introduced a deep composite recommendation framework, VAE–GAN–DCR, designed to enhance educational resource recommendation through the integration of variational autoencoders and generative adversarial networks. Experimental results across multiple benchmark datasets demonstrate that the proposed model consistently outperforms conventional recommendation approaches. In particular, the model achieves notable improvements in Recall@50 on the Netflix dataset, with an average gain of 7.94%, thereby confirming its superior ranking and retrieval capabilities.

By incorporating an item-dependent prior distribution and leveraging discriminator-based feature transfer, the proposed model effectively addresses data sparsity and reconstruction bias, two persistent challenges in traditional recommender systems. This hybrid design enables more accurate modeling of user preferences and enhances recommendation robustness.

Beyond algorithmic performance, this work further validated the pedagogical value of generative AI in smart classroom environments. Comparative educational experiments revealed that students exposed to the proposed system demonstrated significantly stronger creative thinking abilities, especially in adaptability, originality, and precision. Moreover, the experimental group achieved a higher overall creative tendency score (2.61) compared to the control group (2.33), indicating that generative AI not only improves recommendation accuracy but also fosters innovation-oriented learning behaviors.

Overall, the proposed framework exhibits strong adaptability to complex and heterogeneous educational data, providing a technical foundation for personalized learning and precision teaching. Future work will focus on expanding large-scale deployments, exploring multimodal learning analytics, and enhancing real-time adaptability in intelligent educational systems.

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