Intelligent Recommendation System for Music Courses Integrating Ideological and Political Education: Driven by DeepFM Algorithm

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ABSTRACT Personalized course recommendation in higher education requires the simultaneous consideration of learner preferences, semantic content, and educational objectives. This study proposes an intelligent music course recommendation framework based on Deep Factorization Machine (DeepFM) that incorporates ideological and educational value guidance into feature interaction and ranking optimization. Course semantics, student interests, and multidimensional value representations are jointly embedded into a unified feature space, while a value-aware attention mechanism is introduced to strengthen high-order semantic associations and improve recommendation consistency. A joint optimization strategy combining click-through prediction and value relevance further balances personalization with educational objectives. Experimental results demonstrate that the proposed model consistently outperforms conventional recommendation architectures, achieving an AUC of 0.947, an NDCG of 0.936, and a Precision@10 of 0.932 in high-value-density scenarios while maintaining stable value alignment across heterogeneous course categories. Beyond educational recommendation, the proposed multi-feature fusion and attention-driven optimization framework provides a transferable methodology for intelligent information processing and semantic decision-making, offering potential reference for knowledge management and adaptive recommendation services in electromagnetic engineering education and data-centric communication systems.

INDEX TERMS deep factorization machine, intelligent recommendation, attention mechanism, feature fusion, semantic representation

I. INTRODUCTION

CURRENT music course recommendation systems in universities are generally interest-driven and lack ideological and political value modeling, leading to recommendations that deviate from the educational direction, a deficiency also observed in technical fields , where balancing student specialization interests with core educational values like sustainability and ethical production is critical. Music courses have both aesthetic and ideological and political education functions. If intelligent recommendations lack value guidance, it can weaken the educational effectiveness of the education system [1,2]. Solving the problem of the disconnect between interest and value is of practical significance for promoting the integration of aesthetic education and ideological and political education in universities [3,4]. Constructing a recommendation system that combines intelligence and value orientation has become an important direction for educational informatization [5,6].

Existing literature shows that recommending courses in music involves challenges of feature sparsity and the difficulty of extracting value-related semantics from course texts. Collaborative filtering is prone to cold start and bias if there isn't enough behavioral data [7,8]. Content-based recommendation doesn't well identify ideological and political connotations of course texts [9,10]. Even though deep recommendation algorithms form high-dimensional feature interaction structures, they ignore the modeling requirements of value-related characteristics, resulting in a system that focuses on interest matching without regard for educational value goals [11,12].

Enhancements to existing techniques have been geared towards improving model accuracy and feature representation. In collaborative filtering research, latent vector decomposition is used to optimize the performance of the similar item calculation process [13,14]. Content-based semantic recommendation combines topic modeling techniques with document vectorization to enhance text understanding [15,16]. Deep learning-based models, like UserCF and DeepFM, exhibit solid performance with respect to feature interaction and accounted for social attribute factors to reduce recommend biases [17,18]. However, these methods lack quantitative modeling and algorithmic fusion mechanisms for ideological and political value features, and have not yet solved the core problem of synergistic optimization between interest-driven and value-oriented approaches [19,20].

To address the challenges of embedding value features, this paper constructs an intelligent music course recommendation system that integrates ideological and political value guidance. Based on the DeepFM framework, the system semantically encodes course text and lyrics and generates a value feature matrix using an ideological and political value dictionary. Student interests, course content, and value features are uniformly represented by the embedding layer and then input into the model. Low-order interactions are modeled in the factorization layer, and value associations are strengthened through a value attention module in the higher-order network layer. During the training phase, a joint loss function is used to simultaneously optimize click-through rate prediction and value relevance errors, achieving a unified representation and joint optimization of interest features and value features from an algorithmic structure perspective, providing a value-oriented intelligent path for educational recommendation systems, a methodology highly applicable to the curriculum for ensuring technical coursework selection aligns not only with student interest but also with core industry values like resource efficiency and ethical labor standards.

II. DESIGN AND IMPLEMENTATION OF A RECOMMENDATION SYSTEM GUIDED BY IDEOLOGICAL AND POLITICAL VALUES

In the overall design of a recommendation system guided by ideological and political values, the system structure needs to achieve a unified expression of interest features, semantic features, and value features, and use value orientation to constrain the optimization objective, so that the recommendation results maintain a synergistic balance between personalization and ideological and political guidance. To demonstrate the overall logic and methodological hierarchy of the system, the overall architecture shown in Figure 1 is constructed.

Figure 1 illustrates a system that uses multi-source data as input, embedding semantic, interest, and value features to form a unified representation, which is then fed into a DeepFM structure for hierarchical interactive modeling. The lower levels model the relationship between interests and content, while the higher levels introduce a value attention mechanism to enhance value information. The output is optimized using a joint loss function to form recommendation results. A closed-loop feedback mechanism enables dynamic adjustment of interest vectors and value features, maintaining a balance between value orientation and recommendation accuracy during iteration.

DATA PROCESSING AND FEATURE MODELING

The music course text, after being segmented and filtered for stop words, is input into a bidirectional Transformer encoder to obtain a semantic matrix:

$$E_c = f_{\text{enc}}(T; \theta_e) \in \mathbb{R}^{n \times d_c} \tag{1}$$

In formula (1), T represents the course word sequence, f_{enc} represents the semantic encoding function, θ_e represents the model parameters, and d_c represents the content feature dimension. The course content vector is formed through pooling and normalization operations v_c.

Student interest features are generated from historical behavior sequences. Let the click sequence be denoted as $H_u = \{c_1, \dots, c_m\}$, which is mapped to a vector set through an embedding matrix $\{h_1, \dots, h_m\}$ and aggregated by behavior weights.

$$v_u = \sum_{i=1}^{m} \alpha_i h_i, \quad \alpha_i = \frac{\exp(\beta s_i)}{\sum_{j=1}^{m} \exp(\beta s_j)} \tag{2}$$

In formula (2), s_i is the standard score of click frequency, and β is the interest concentration coefficient. This method suppresses random behavior interference and strengthens the significant terms of preference [21,22].

The value characteristics of ideological and political education are mutually mapped by the embedding of course semantics and value lexicon. The value lexicon is constructed from six value themes that form the foundation of the multidimensional value representation, and contains a fixed set of lexical items aligned to these themes. Each lexical item is manually validated to ensure semantic relevance to course texts, and the lexicon maintains a consistent structure across all semantic processing stages to preserve the stability of the value distribution during embedding. The lexicon matrix organizes the six value dimensions into a unified embedding space, and each dimension is represented as a dense vector aligned with the semantic encoder output. The resulting value vector forms a six-dimensional representation linked to the themes of patriotism, collectivism, social responsibility, aesthetic education, innovative spirit and cultural identity, and the structural alignment ensures that each dimension maintains a stable position during the interaction between semantic content and value mapping. A lexicon matrix $M_v \in \mathbb{R}^{K \times d_v}$ is defined, and the semantic response of the course in each value dimension is calculated:

$$p_v = \text{softmax}(E_c M_v^\top) \tag{3}$$

In formula (3), K is the number of value topics, and p_v is the value probability distribution. The weighted vector is fused across semantic segments. The feature mapping process establishes a direct correspondence between the contextualized semantic outputs and their value activations by projecting the lexicon matrix through a similarity-based transformation. This transformation assigns continuous activation strengths to the six value dimensions, and the

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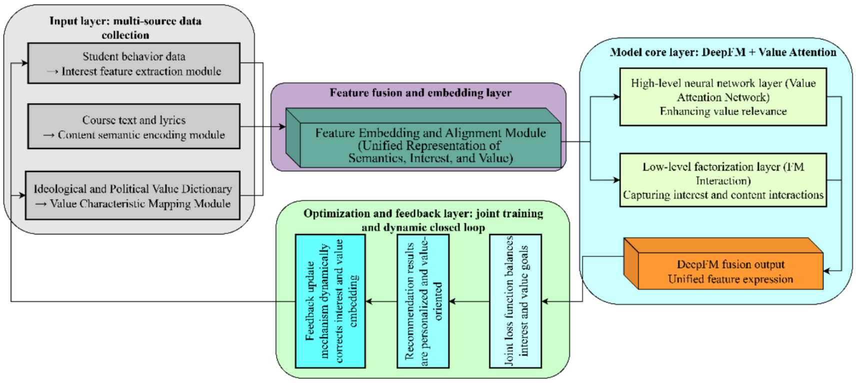

FIGURE 1. Overall architecture of the intelligent recommendation system for music courses guided by ideological and political values

responses are integrated across segments to form a stable value distribution. When value-related expressions are sparse, semantic activation is triggered through a similarity threshold, and the resulting distribution may shift due to the limited density of explicit cues. To reduce this effect, sparsity filtering is applied to low-frequency responses, and the remaining activations are aggregated through paragraph-level averaging to maintain coherence in the value representation. This process allows texts with low explicit value content to generate consistent implicit value signals that remain usable during feature alignment and interaction modeling.

The three types of features are linearly mapped to a unified dimension to form a fused input:

$$x_i = W_c v_c + W_u v_u + W_v v_v + b \tag{4}$$

In formula (4), W_c, W_u, W_v are the mapping matrices, b is the bias term, and the resulting feature vector x_i constitutes the DeepFM input, realizing the structured alignment of semantics, interests and values [23,24]. During the alignment process, the value vector compresses features from different sources to a unified dimension through linear mapping, making the distribution structure of the value dictionary, the output distribution of the semantic encoder, and the embedding distribution of interest features comparable in the same space, thus avoiding the impact of scale inconsistencies between different feature sources on the subsequent interaction modeling process.

DEEPFM FUSION AND VALUE ATTENTION MECHANISM

The fused feature vectors x_i are input into a factorization layer, which captures the low-order correlation between interests and course content through second-order interaction. The output of the second-order interaction is defined as follows:

$$y_{\mathrm{FM}} = \sum_{f=1}^{d_x} \sum_{f'=f+1}^{d_x} \langle v_f, v_{f'} \rangle \, x_{i,f} x_{i,f'} \tag{5}$$

In formula (5), $v_f \in \mathbb{R}^k$ is the embedding vector of f-th dimension, d_x is the dimension of the input vector, and $\langle \cdot, \cdot \rangle$ represents the inner product operation. This operation explicitly models the second-order interaction of features, so that the relationship between latent interest patterns and course content can be preserved at the lower level [25,26].

Higher-order nonlinear interactions are achieved through a multi-layer feedforward neural network. The network input is given by x_i, and value attention weights α_v are introduced in each hidden layer. The calculation formula is as follows:

$$h^{(l)} = \sigma \left(W^{(l)} h^{(l-1)} \odot \alpha_v + b^{(l)} \right) \tag{6}$$

In formula (6), $h^{(0)} = x_i$, $W^{(l)}$ and $b^{(l)}$ are the weight matrix and bias vector of the l-th layer, respectively, σ is the activation function, and $\odot$ represents the element-wise multiplication operation. α_v is obtained by linear transformation and softmax normalization of the course value vector v_v, and is used to dynamically adjust the response intensity of each hidden unit to the value feature. This mechanism enables the network to strengthen value information while capturing complex nonlinear interactions, and ensures that the model still maintains the salience of ideological and political orientation in high-order representation [27,28]. The DeepFM output is obtained by a linear combination of low-order interactions y_{FM} and high-order network outputs y_{DNN}:

$$\hat{y}_i = y_{\mathrm{FM}} + y_{\mathrm{DNN}} \tag{7}$$

In formula (7), $\hat{y}_i$ represents the final predicted score. This integration appropriately employs the interest, content, and value features at different levels, allowing for an adequate representational foundation for the joint optimization step. Simultaneously, during the training stage, embedding and attention weights are automatically adjusted through backpropagation, adaptively strengthening the dependence of higher-order networks on value features and enhancing the recommendation system's sensitivity to ideological and political goals [29,30].

JOINT OPTIMIZATION AND SYSTEM CLOSED-LOOP DESIGN

During the model training phase, click-through rate prediction and value relevance are integrated into a unified loss function to ensure that recommendations both satisfy personalized interests and strengthen ideological and political guidance. The click-through rate prediction loss is defined as a cross-entropy form:

$$L_{\mathrm{CTR}} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)] \quad (8)$$

In formula (8), N is the sample size, y_i is the actual user-clicked tag, and $\hat{y}_i$ is the model-predicted click probability. Value fit i s c alculated u sing t he c osine s imilarity between the course value vector v_v and the user's potential value preference vector, and the value loss is defined as a negative logarithmic form:

$$L_{\mathrm{Val}} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{v_v^{\top} {v_u}^{v}}{\|v_v\|\|{v_u}^{v}\|} \quad (9)$$

In formula (9), v_v is the course value vector, and $\|\cdot\|$ is the Euclidean norm operation. The joint loss function is synthesized with proportional weights:

$$L = L_{\mathrm{CTR}} + \lambda L_{\mathrm{Val}} \quad (10)$$

In formula (10), the hyperparameter λ for adjusting the strength of value constraint is set to 0.65 through experiments to balance click-through rate and value fit. λ has a direct impact on the gradient distribution, ensuring that the weight ratio of value features and interest features in the training process remains a controllable update structure. In sparse value scenarios, this weighting leads the optimization to emphasize value consistency more strongly, which can marginally suppress CTR-oriented updates. The loss function updates the embedding vector, attention weight and fully connected layer parameters synchronously during backpropagation, so that both low-order interaction and high-order attention network participate in value enhancement [31,32]. The training process achieves model parameter convergence through iterative gradient descent, and the output prediction score is fed back to the recommendation strategy generation module to form a closed loop [33,34]. The closed-loop system adjusts the interest embedding and value vector in real time when the user behavior is updated, ensuring that the recommendation is dynamically corrected according to learning preferences and value needs, while providing quantifiable feedback signals for subsequent performance evaluation, and maintaining the continuous optimization of the recommendation system in personalization and ideological and political value guidance [35].

EXPERIMENT AND EVALUATION

The university music course learning platform provides the experimental data and consists of three types of information: course text, student course selection behavior, and course-related tags. The dataset contains eight hundred and sixty-four music course instances, spanning six course categories, with student behavioral records derived from fourteen thousand five hundred and twenty-one valid selection logs after cleaning. The platform user base involved in the experiment consists of two thousand three hundred and sixteen unique learners, and all data are retained in their original structural granularity to ensure consistency between modeling and real usage conditions. After performing semantic cleaning and feature normalization, a composite feature set of interest vectors, semantic vectors, and value vectors is derived. The ideological and political value dictionary used for generating the multidimensional value vector is constructed through a standardized lexical compilation process grounded in widely adopted higher-education value descriptors. The dictionary terms are expanded and verified through cross-textual alignment within the university's teaching resources, ensuring that the semantic cues remain consistent with the general normative framework of ideological and political education. The finalized dictionary forms a unified reference for value encoding across all course texts without introducing institution-specific deviations. A stratified sampling method is used in the system training to sample the dataset, modeling, and evaluation takes place on a dataset split, where 70% is a training set, 15% is a validation set, and 15% is a test or evaluation dataset. Four comparative models are set - Factorization Machine (FM), Wide & Deep, DeepFM, and DeepFM + Value Attention - which are chosen to compare the impact of various feature fusion techniques on the recommendation performance. The evaluation of the models is reported using several metrics (AUC, NDCG, Precision@10) to demonstrate the recommendation model's performance in terms of ranking accuracy and recommendation precision. A value fit metric is also reported to assess the level of agreement of the recommendation output with the ideological and political value of the course. The experiment is conducted on a common hardware and software environment. The parameters settings are fixed to prevent any variation of conditions after being optimized using the validation set to facilitate reproducible research. All model training iterations are also terminated using the same stopping criteria to mitigate against overfitting.

III. RESULTS ANALYSIS

RECOMMENDED PERFORMANCE ANALYSIS

This experiment involves comparing the recommended performance of multiple models that follow different types of music course to assess the impact of embedding ideological and political value features. The six courses are categorized according to the density of ideological and political value content in the course text. Value density is quantified as the proportion of semantic segments that match terms in the ideological and political value lexicon relative to the total number of semantic segments after preprocessing and embedding. High-density courses have a larger proportion of segments with value-related terms, medium-density courses have an intermediate proportion, and low-density courses have few segments with detectable value content. This quantification establishes an objective metric for evaluating the influence of value features on recommendation performance. Model 1 is FM, which explicitly relies on low-order interactions on features. Model 2 is Wide & Deep, which combines linear memory and a non-linear expression. Model 3 is DeepFM, which inherits both the linear and non-linear structures, with features unified under the embedding layer of the model. Model 4 is the proposed DeepFM + Value Attention model, which embeds a value attention mechanism and multi-dimensional value vectors, as part of the DeepFM framework, which provide the capacity to observe changes to the correlation to interest and value. The experiment covers six types of courses: Appreciation of Red Classics (C1), Revolutionary Song Composition Practice (C2) (high value density), History of Chinese National Music (C3), History of Western Classical Music (C4) (medium density), Popular Music and Society (C5), and Film and Television Music Production (C6) (low density), forming a top-down value semantic gradient, providing a validation basis for the model performance under different ideological and political contexts. The results are shown in Figure 2. This classification based on lexicon-driven value density allows the comparison of model performance across courses with systematically varying levels of ideological and political content, providing a structured basis for interpreting differences in AUC, NDCG, and Precision@10 metrics.

The results show that the model in this paper performs best in high-value-density courses. The AUC for the "Appreciation of Red Classics" course is 0.947, NDCG is 0.936, and Precision@10 is 0.932, representing improvements of 0.019, 0.025, and 0.030 respectively compared to DeepFM, demonstrating the enhanced effect of the value attention mechanism in the fusion of semantics and value. For the "Revolutionary Song Creation Practice" course, the three indicators are 0.941, 0.926, and 0.918, all higher than DeepFM. For the medium-density course "History of Chinese Folk Music," the AUC is 0.923, close to DeepFM's 0.918, while the NDCG is slightly lower by 0.004, indicating that the effect of value features weakens as semantic density decreases. In the low-density course "Popular Music and Society," DeepFM's AUC is 0.907, slightly higher than the model in this paper's 0.905, while the difference in Precision@10 is only 0.002, indicating that interest features are more dominant. The sparse activation of value-related semantics increases the relative weight of the value constraint in the joint loss, which slightly reduces the contribution of the CTR objective during training and results in the small AUC drop. Overall trends indicate that value embedding structures have significant advantages in scenarios with high semantic and high value coupling, and their performance improvement stems from the discriminative power of value features and the stable optimization of the model at the feature interaction layer. In low-density courses, the reduced value activation causes the joint loss to tilt slightly toward value preservation, narrowing the optimization space of the CTR objective and producing minor performance loss.

EFFECT OF IDEOLOGICAL AND POLITICAL VALUE GUIDANCE

This experiment compares the course fit performance of different recommendation models under multidimensional ideological and political value dimensions, examining the models' ability to capture value signals in courses with high and low value densities. Four models are included in the comparison to construct a complete value alignment structure. Model 1 is a lexicon-matching structure, which forms value responses through the co-occurrence strength between course text segments and the value lexicon. Model 2 is a content-based semantic similarity structure, which constructs the course–value relation through cosine similarity between course semantic vectors and value vectors. These two models provide static representations of value fit and reflect the alignment effect formed by direct text–value associations. Model 3 is DeepFM, which focuses on the modeling ability of low-order and high-order interactions after unifying features in the embedding layer. Model 4 is DeepFM + Value Attention, which introduces multidimensional value vectors and an attention mechanism to strengthen the dynamic correlation between interest features and value features. The experiment covers six types of courses: appreciation of red classics, practice of revolutionary song creation, history of Chinese national music, history of Western classical music, popular music and society, and film and television music production (C1–C6), corresponding to the value dimensions of patriotism, collectivism, social responsibility, aesthetic education, innovative spirit, and cultural identity (V1–V6). Through visualization analysis of the fit of each type of course under each value dimension, the differences in model performance under different semantic and value density conditions are presented. The results are shown in Figure 3.

The lexicon-matching baseline shows a clear dependence on explicit value phrases, producing concentrated responses in high-density texts such as "Appreciation of Red Classics," while presenting a notable reduction in discrimination in medium- and low-density courses. The content-based similarity model exhibits a more balanced distribution than the lexicon-based structure, with higher alignment scores across all dimensions, yet its variation trend remains highly correlated with the density of value expressions. Compared with these two static alignment structures, DeepFM yields more stable responses across dimensions by virtue of unified feature embeddings, and the improvements become more evident in high-density courses. DeepFM + Value Attention showed a significant enhancement in the alignment of high-value-density courses like "Appreciation of Red Classics"

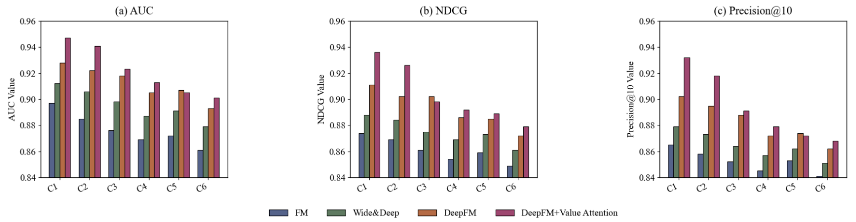

FIGURE 2. Comprehensive performance of different recommendation models across three metrics for six types of courses. (a)AUC, (b)NDCG, (c)Precision@10

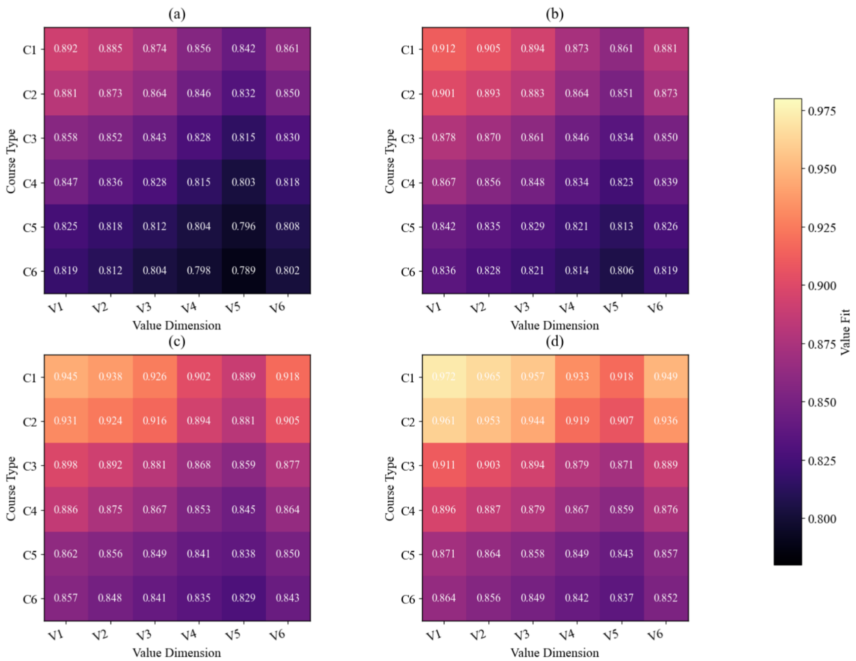

FIGURE 3. Heat map distribution of ideological and political value alignment of different models under six types of courses and six value dimensions. (a) Lexicon-Matching baseline, (b) Content-Based Similarity baseline, (c) DeepFM model, (d) DeepFM + Value Attention model

with the dimensions of patriotism, collectivism, and social responsibility (0.972, 0.965, and 0.957), compared to DeepFM's 0.945, 0.938, and 0.926. A similar trend is observed in "Practice of Revolutionary Song Composition." The medium-density courses "History of Chinese Folk Music" and "History of Western Classical Music" both show approximately a 0.012 increase in key dimensions relative to DeepFM, and the auxiliary dimensions remain stable. In low-density courses such as "Popular Music and Society" and "Film and Television Music Production," the improvement remains slight, as interest features dominate the interaction layer, and the value signal weakens. Overall, the two simple models form value alignment distributions strongly constrained by text density, whereas DeepFM and DeepFM + Value Attention exhibit more consistent responses across value dimensions. The attention mechanism produces a generalized enhancement for high-density courses while maintaining stability in medium- and low-density scenarios, achieving a balanced coupling of value guidance and recommendation accuracy.

ABLATION EXPERIMENT

To examine the roles of value modeling, attention mechanisms, and joint optimization in recommendation performance and value alignment, six model architectures were designed: Model Architecture 1 is a basic DeepFM model, containing only interest and content feature interactions; Model Architecture 2 introduces value embedding at the input layer to achieve multi-dimensional feature fusion; Model Architecture 3 adds a single-layer value attention layer to a higher-order network; Model Architecture 4 combines value embedding and attention mechanisms; Model Architecture 5 introduces a joint loss function to balance click-through rate prediction and value consistency; Model Architecture 6 is a complete model that integrates embedding, attention, and joint loss to achieve dynamic coupling of interest and value. All models were trained under the same data and hyperparameter conditions, and the results are shown in Table 1.

TABLE 1. Ablation experimental results of different model structures

Model Number	AUC	NDCG	Precision@10
M1	0.864	0.852	0.841
M2	0.878	0.867	0.853
M3	0.890	0.879	0.864
M4	0.904	0.892	0.879
M5	0.915	0.903	0.888
M6	0.922	0.903	0.893

The results show that performance gradually improves with structural complexity. DeepFM's AUC is 0.864, and Precision@10 is 0.841, reflecting the limitations of interest features in the absence of a value dimension. The addition of value embedding increases NDCG by approximately 0.015, indicating that the mapping between course semantics and ideological and political elements enhances ranking relevance. The attention mechanism further strengthens the allocation of higher-order semantic weights, raising the AUC to 0.890. The joint loss helps the model learn to stabilize when balancing the two types of objectives, while the complete model has the best overall performance with an AUC of 0.922, NDCG of 0.903, and Precision@10 of 0.893, demonstrating the core significance of the synergistic effect of value embedding and multi-layer attention in guiding ideological and political values.

PARAMETER SENSITIVITY ANALYSIS

In the parameter stability testing phase of the model, the stability of the DeepFM + Value Attention model under the fusion of value and interest was tested by adjusting the learning rate, the number of hidden layer nodes, and the L2 regularization coefficient. The learning rate affects the gradient convergence speed, the number of hidden layer nodes determines the feature abstraction ability, and the L2 coefficient is used to suppress weight overfitting. Each parameter was set to values in intervals under fixed training conditions, and the changing trends of AUC, NDCG, and Precision@10 were observed. The results are shown in Figure 4.

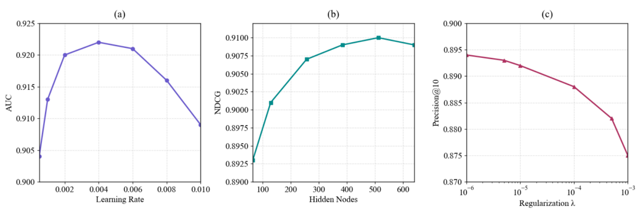

FIGURE 4. Parameter sensitivity analysis of the DeepFM + Value Attention model. (a) Learning rate, (b) Number of nodes, (c) Regularization coefficient

The model exhibits a discernible stability range under parameter variations. The learning rate affects the convergence rate and gradient update accuracy; when set to 0.004, the AUC reaches 0.922. A lower rate leads to learning stagnation, while a higher rate causes performance degradation due to oscillations. Increasing the number of nodes strengthens feature representation; NDCG increases from 0.893 to 0.910 when increasing from 64 to 512, but stagnates after further expansion to 640, reflecting the saturation boundary of network complexity. The regularization coefficient λ adjusts the weight sparsity; Precision@10 is 0.894 at 1.0×10^{-6}, but drops to 0.875 after the penalty increases to 1.0×10^{-3}, indicating that excessive constraints weaken feature discriminative power. Training was conducted with different values of λ. The results showed that the lower the value, the weaker the value matching, and the ranking indicators remained in a range similar to that of valueless modeling. As the value increased, the value matching score rose, and the ranking indicators remained stable in the middle range. When the value was too high, the proportion of value signals increased, and the ranking indicators decreased. This trend reflects the moderating effect of λ on the two types of error distributions in the joint objective. Overall, the results show that the model achieves optimal performance and robust convergence with a moderate learning rate, appropriate network depth, and balanced regularization. The variation of λ exhibits a continuous range, resulting in a stable compromise trajectory between value matching and ranking accuracy.

IV. CONCLUSION

This paper constructs a music course recommendation system integrating ideological and political values based on DeepFM, embedding course semantics, student interests, and value characteristics in a unified manner, and strengthening value association through a value attention mechanism. Experimental results show that the AUC of the red classics appreciation course is 0.947, NDCG is 0.936, and Precision@10 is 0.932, which is higher than the baseline model in the same scenario. The patriotism dimension fit increases from 0.945 to 0.972 under high value density, and the model forms a stable structure that maintains the consistency between ranking accuracy and value alignment. The method forms a unified interaction mechanism among semantic features, interest features, and value features, and supports the integration of ideological and political orientation into personalized recommendation processes in university music education. The modeling structure provides a technical path that maintains the balance between individual learning preferences and value guidance, and offers a scalable framework that can extend to curriculum systems in related disciplines where content semantics, learner interests, and value orientation require joint representation and optimization.

AUTHOR CONTRIBUTIONS

Han Yan designed, collected and analyzed the data, and drafted the manuscript. Han Yan conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Han Yan participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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