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Modeling Elderly Dance Interest Preferences and Developing a Dynamic Course Adaptation System Using LightGBM

Yalin Cui
Ph.D. Candidate, Taizhou University, Taizhou, Jiangsu, 225400, China, E-mail: cuiyalin0222@163.com

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Abstract: Traditional methods for recommending dance courses for the elderly, due to their static modeling, struggle to adapt to the dynamic changes in senior's interests, resulting in insufficient course matching accuracy. This paper constructs a Light Gradient Boosting Machine (LightGBM) preference prediction model that leverages temporal feature enhancement and dynamic weight updates and designs a dynamic course adaptation system based on this model. This method extracts statistical and trending features from user behavior sequences through a sliding window to quantify interest drift. The model iteratively fits the residuals of preference labels using a forward distribution algorithm and gradient-boosted decision tree principles, and an exponential decay-based weight update mechanism is applied during the online learning phase to enable the model to continuously track interest evolution. Experimental results show that the model achieves prediction accuracies of 0.328 and 0.426 for the two core indicators, course click-through rate and user satisfaction, respectively. This research provides a highly adaptable and engineering-feasible technical path for optimizing service operations in elderly education, offering a reliable example of adaptive resource allocation and personalized service delivery.

Keywords: Senior dance, interest preference modeling, course recommendation, Light Gradient Boosting Machine (LightGBM) model, dynamic adaptation.

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1. Introduction

With the global trend of population aging, spiritual and cultural life, and the physical and mental health of the elderly, these issues have become increasingly important foci of social attention. Elderly dance courses are considered an excellent way to improve the lives of older adults by combining art, fitness, and Social Interaction (Sánchez-Alcalá et al., 2024; Britten et al., 2023). However, the traditional method of delivering dance Course training is inadequate to address the diverse and rapidly changing needs of older adults, resulting in lower participation and sustainability rates in these courses. Developing an intelligent system to adapt dance program courses to better align with the interests and preferences of older adults offers significant practical opportunities to enhance the quality of education services for older adults and support the concept of "active aging" (Gronek et al., 2021; Hansen et al., 2024). The intent of this manuscript is to outline the development process for an adaptation system for a dance program, thereby improving the potential to enrich the cultural, physical, and mental well-being of older adults. From an operations management perspective, such a system can optimize the allocation of limited educational resources by dynamically matching course offerings to evolving user demands, thereby improving both operational efficiency and service effectiveness. From a service operations management perspective, dance course delivery can be viewed as an adaptive service system, a class of systems that dynamically adjust service offerings based on evolving user needs and feedback. Within this framework, the challenge of matching course supply to fluctuating demand aligns closely with the principles of demand-driven service operations, in which real-time user interactions serve as signals for continuous service reconfiguration.

There are multiple major barriers to achieving accurate course recommendations based on existing research methods for seniors/ older adults. The elderly's interests and preferences are influenced by multiple factors (e.g., age, health condition, and prior experiences) as well as by processual behavior (e.g., the courses clicked, whether the course was completed, and how the course was rated). These processual or time-based behaviors yield vital insights into how one's interests may change over time. Therefore, it is impossible to effectively use static modeling techniques to capture this change, or "drift of interest," over time (Jiang and Zeng, 2022; Chen et al., 2023). Additionally, the use of sparse, highly heterogeneous data arising from the substantial number of elderly users poses challenges for model training (Choi et al., 2023; Zhai et al., 2023). The ideal recommendation platform must have an ongoing learning function that continuously updates its preferences for the user through their interactions, rather than relying solely on offline training (Ahmadian Yazdi et al., 2024; Wang, 2025).

To address the challenges in each of these areas, previous research has examined different approaches. Collaborative filtering methods heavily rely on the density of the user-course interaction matrix to generate recommendations. Therefore, they become less accurate when the dataset is sparse (based on user and course data) (Panteli and Boutsinas, 2023; Abdalla et al., 2023). Content-based filtering does help alleviate the cold start issue, however, due to the limited availability of manually created feature sets, it is hard for researchers to mine deeper latent interest associations from single features (Phalle and Bhushan, 2024; Ramadhan and Musdholifah, 2021). Researchers use matrix factorization or traditional machine learning models (e.g., logistic regression) yet still fail to capture nonlinear and complex relationships among features (Mao et al., 2024; Kyriazos and Poga, 2024). Current deep learning research can be used to create models to generate recommendations based on user interest. However, deep learning methods require extensive training time, access to vast amounts of data, high-performance hardware, and substantial funding for hardware and software development, posing challenges for practical use and performance optimization (Taye, 2023; Scorzato, 2024). The majority of the studies referenced share a downside. They treat user's interests as static labels and provide no quantitative measure of the dynamic evolution of interests over time.

This paper presents a LightGBM model for tracking change over time and dynamically developing aged interest profiles from existing methods in dynamic modeling and continual adaptation. Using the proposed model, it built an end-to-end system that models the aged dance interest profile and continually adapts dance courses based on user feedback. It first combined user-specific static data and dynamic interactions through feature engineering. In feature engineering, it also emphasized the ability to extract time-varying statistical features and trending indicators from the user's historical sequence of behaviors using a sliding time window technique. Subsequently, we applied our LightGBM model with gradient boosting decision trees to learn the intricate relationships that the user's features have with their preference labels. Once the system has been deployed, it has developed an online-learning pipeline that periodically uses recently produced user data as an updated incremental training set and uses the principle of exponential decay when adjusting the sample weights in the sample weight update strategy to rescale the parameters of the model, allowing the system to efficiently learn and retain both new information and historical patterns. The prototype of a dynamic course adaptation system constructed in this research exemplifies how engineering solutions can support elderly education by integrating predictive modeling with adaptive service operations, balancing accuracy, adaptability, and operational efficiency. This work is theoretically grounded in adaptive systems theory, which posits that systems capable of sensing environmental changes and adjusting their internal states achieve superior long-term performance. By framing the elderly dance education platform as an adaptive service system, we operationalize this theory through a LightGBM-based preference model that continuously updates its parameters in response to new user interactions.

2. A Dynamic Preference Modeling and Adaptation Method Based on LightGBM

2.1. Data Source and Time Series Characteristic Engineering

The following types of databases create the foundation of the system utilized by the elderly dance education platform, which includes registration information, course metadata, and user interaction logs. Feature engineering on both static and dynamic heterogeneous data sources takes place to enable the creation of a dynamic preference modeling feature of the system. Three types of user attributes are static: age, gender, and self-reported health status. Each of these attributes was converted into numerical vector representations using one-hot encoding and min-max normalization (Ali, 2022; Yu et al., 2022). In addition to the static user attributes, course metadata, which includes the dance type(s), intensity level(s), and length of lesson(s) for each course, was standardized and encoded as well.

User interest drift can be modeled using dynamic behavioral characteristics. The original behavior log has 4 fields: user ID, course ID, behavior type, and timestamp. In order to model the change in a user's interest over time, this approach applies to a fixed-length (e.g., 6 months) 'sliding' time frame, which looks at all behaviors by that user in chronological order. For the behaviors within this time frame, three types of statistics are calculated. 1) Total value and standard deviation of behavior frequency, 2) Value of the daily average behavior intensity trend, and 3) A weighted average of the last behaviors. For trend calculation, linear regression is used to fit the data points to a graph, and the trend's slope indicates whether the user is gaining or losing interest in a particular course in this time frame (Eq. (1))

$$\mathrm{Trend} = \frac{n\sum_{i=1}^{n}\left(t_i \cdot x_i\right) - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} x_i}{n\sum_{i=1}^{n} t_i^2 - (\sum_{i=1}^{n} t_i)^2} \tag{1}$$

In Eq. (1), n represents the number of actions within the window. t_i is the normalized time of the i-th action relative to the window's starting point, and x_i represents the quantified value of the i-th action (such as a rating or completion indicator). The sign and magnitude of this slope directly reflect the rate and direction of change in user interest over a period of time. Finally, the complete feature system constructed from the three dimensions of user, course, and interaction is shown in Table 1.

Static and dynamic feature vectors are concatenated at the sample level to form the final feature representation of each user-course pair, which serves as the input to the subsequent LightGBM model.

Table 1. Description of feature system

Feature category	Feature name	Feature description	Processing & Calculation method
User static features	Age	User's actual age	Min-Max normalization
	Health status	Self-reported health level	One-Hot encoding
Course static features	Dance genre	Category of the dance course	One-Hot encoding
	Intensity level	Physical activity intensity of the course	Label encoding
User-Course dynamic features	Recent click-through rate	Frequency of recent course click behaviors	Sliding window count statistics
	Average completion rate	Proportion of course videos fully watched	Mean value within sliding window
	Rating trend	Linear change of user's recent ratings	Linear fitting based on time series
	Behavior sequence weight	Comprehensive influence of recent behaviors	Weighted sum based on time exponent

2.2. Static Preference Modeling based on Temporal Enhancement LightGBM

Based on the fused feature vectors output by feature engineering, the goal of this stage is to build a powerful static baseline model, that is, to establish an initial mapping function to predict the probability $\hat{y}$ of a user's interest in unlearned courses by learning the temporal patterns in historical data. The LightGBM model adopts an additive training strategy and a forward distribution algorithm to approximate this optimal function by iteratively generating K decision trees. Its final prediction output is the sum of the prediction from all trees (Ororbia and Mali, 2023; Hajihosseinlou et al., 2023), as shown in Eq. (2).

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \tag{2}$$

In Eq. (2), $\hat{y}_i$ represents the predicted value of the i-th sample. f_k represents the k-th decision tree, and $\mathcal{F}$ is the space of all decision trees. The goal of each iteration is to find a new tree f_k that minimizes the specified loss function $L(y_i, \hat{y}_i^{(k-1)})$. The model is optimized in the function space by gradient descent (Yao et al., 2023; Tian et al., 2023). The calculation method of the negative gradient (i.e., residual) r_{ik} of the current model is shown in Eq. (3).

$$r_{ik} = -\left[\frac{\partial L\left(y_i, \hat{y}_i^{(k-1)}\right)}{\partial \hat{y}_i^{(k-1)}}\right] \tag{3}$$

The construction of the new tree f_k aims to fit these residuals r_{ik}. LightGBM improves training efficiency and processing power for high-dimensional data by applying two core techniques. Gradient one-sided sampling retains all large gradient samples when calculating information gain and only randomly samples a small gradient sample subset, which makes the estimation of information gain more focused on samples that are not well fitted by the current model. Mutually exclusive feature bundles those features in high-dimensional sparse features that are not simultaneously non-zero, thereby merging multiple features into a single feature, significantly reducing feature dimensionality and data storage overhead (Gu et al., 2023; Zhang et al., 2023). The above process trains a high-performance static preference-prediction model using historical data. This model makes full use of temporal features and provides a high-performance, clearly comparable benchmark for the subsequently applied dynamic update mechanism. The above model and the subsequent online update mechanism together constitute a complete dynamic adaptation system, and its overall architecture and data flow are shown in Fig. 1.

Fig. 1 illustrates the end-to-end process of data from multi-source input to personalized recommendation output. The raw data is processed by the feature engineering layer, where user behavior logs are transformed into indicators of quantified interest evolution through a dedicated time-series dynamic feature construction module, and then concatenated with static user and course features. The LightGBM-recommended prediction model at the core of the architecture generates the initial list of course recommendations from the fused feature vector. This system also employs a dynamic weight update mechanism that uses real-time feedback to adaptively update the model's parameter values as part of ongoing learning. It also encompasses the entire process, so that all parts are interrelated, including feature engineering, model prediction, and feedback optimization through feedback loops that adaptively modify its predictions as the user changes their interests

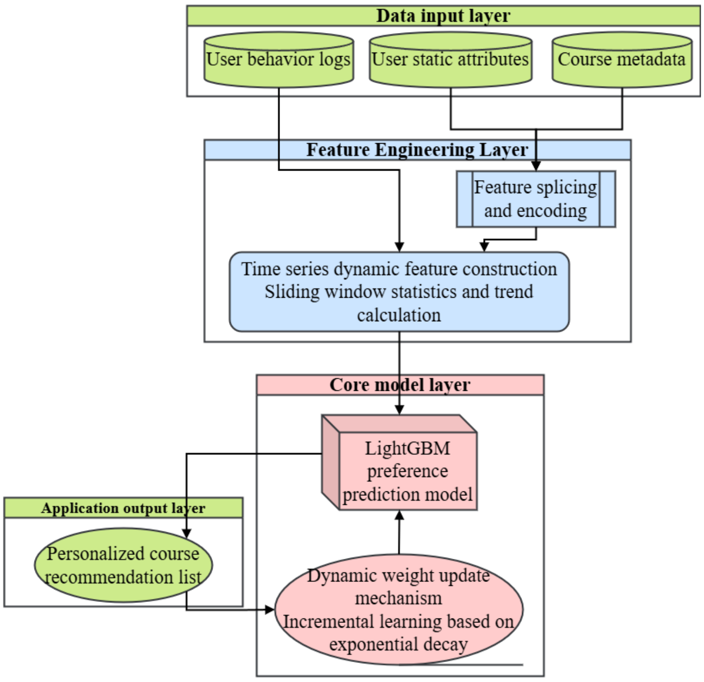


Fig. 1. Dynamic course adaptation system architecture

To train the model, it employs a loss function of negative log-likelihood L (normalized over all examples) (Zhang et al., 2022; Liu et al., 2024), which is defined by Eq. (4) below. In this equation (4), $y_i \in \{0,1\}$ is the true label of the user's interest in the course.

$$L\left(y,\hat{y}\right) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log\left(\sigma\left(\hat{y}_i\right)\right) + \left(1-y_i\right)\log\left(1-\sigma\left(\hat{y}_i\right)\right)\right] \tag{4}$$

The function $\sigma(\cdot)$ in Eq. (4) is a Sigmoid function that converts the model output $\hat{y}_i$ into a probability value between zero (0) and one (1) (Zaidi and Al Luhayb, 2023; Mishra et al., 2021), and N is the total number of training samples in the static baseline model. The model receives as input the features that were combined to create this baseline, which included time-variant or time-based features intended to simulate changes in a user's preferences over time, and the model's output is equivalent to $\sigma(\hat{y}_i)$, the likelihood that the user is interested in a particular course. The probability value generated is used by the recommended algorithm to sort the personalized course recommendations for each user.

2.3. Tracking Dynamic Preference Evolution based on Online Learning

The design of the online learning mechanism is informed by adaptive control theory, which emphasizes balancing exploration and exploitation in dynamic environments. In service operations, this translates to maintaining stability by retaining historical patterns while enabling responsiveness by integrating new feedback. An initial LightGBM model has been established and is running in an online service with an automatic, dynamic method to adapt models to shifts to user preferences over time. To accomplish this, it uses an exponential decay-based method (Zhao and Hua, 2024; Zarrinkalam et al., 2024) and retrains the model at regular intervals, collecting newly generated interaction data at scheduled intervals. The current retraining process is done using the newly collected data to produce an incremental training set. To balance the need to maintain significant historical patterns with the need to integrate emerging trends, we use a weighted loss function during retraining that assigns a weight based on each sample's age. As such, for a specific sample, the weight (w_i) at which the sample is retrained is determined according to the exponential decay rule defined by Eq. (5).

$$w_i = \lambda^{t_{current}-t_i} \tag{5}$$

In Eq. (5), $t_{current}$ signifies the current point in time, and t_i indicates when the i-th interaction was sampled. The time difference between $t_{current}$ and t_i indicates how long ago the sample was taken. The decay factor λ, which is defined as a hyperparameter ($0 \leqslant \lambda \leqslant 1$), determines how quickly the model forgets about or drops out the older samples. When λ is closer to 1, the model retains more of its historical samples for longer periods of time; when λ is smaller, it drops the samples at a much faster rate. The weighted age of each sample is added into the weighted negative log-likelihood loss developed in Eq. (6), which is defined as L_w.

In Eq. (6), N represents the total number of samples in the current training dataset. The training dataset consists of new samples, combined with a sample of historical samples, for the purpose of training the model to minimize the weighted loss L_w.

$$L_w = -\frac{1}{N}\sum_{i=1}^{N} w_i \cdot \left[y_i \log\left(\sigma\left(\hat{y}_i\right)\right) + (1-y_i)\log\left(1-\sigma\left(\hat{y}_i\right)\right)\right] \quad (6)$$

The training model goes through multiple rounds of this training cycle and consequently continues to adjust the parameters of the model with respect to the changing nature of user interests to enable the delivery of relevant recommendations with respect to time going forward.

3. Experimental setup and evaluation

3.1. Dataset and Experiment Setup

Researchers assessed the efficiency of this newly developed technique by validating it using a publicly available dataset from a large online website for older adults learning about dance classes. The public dataset contained a total of 850,000 entries from online interactions among approximately 15,000 unidentified older adults who viewed dance classes and their associated materials from January 2022 to 30 June 2023. To simulate a realistic recommendation environment, the researchers divided the data based on its actual time. First, they used the first 12 months of data to build and train the model. Second, they used the next 3 months of data for hyperparameter validation (to confirm optimal agreement), and third, they used the next 3 months of data as the test dataset for the final evaluation. The results of these experiments were representative of the model's ability to forecast user behavior in the future. A detailed overview of the dataset used is located in Table 2, which provides statistical information regarding user characteristics, course metadata, and user activity logs from over 850,000 users.

Table 2. Basic statistical information of the dataset

Statistical item	Value
Number of users	15,682
Number of courses	487
Total interaction records	856,341
Data collection time range	2022.01 - 2023.06
Training set time range	2022.01 - 2022.12
Validation set time range	2023.01 - 2023.03
Test set time range	2023.04 - 2023.06

Table 2 is well organized and summarizes the experimental dataset. The columns refer to the scale of the experiments and the time frame they captured. For example, the interaction logs allowed for a wide range of diverse ways in which users act (clicks, completed courses, and ratings) that would serve as a good base for creating models of how user's personal interests and preferences change and develop over time.

The experimental setup was based on a server with Intel Xeon E5 CPUs with 64 GB of memory, built within a Python 3.8 environment using the core modeling framework of LightGBM v3.3.2. The hyperparameters for training were selected through a grid search on the validation set. The optimal learning rate was set to 0.05, the maximum tree depth was set to 7, and at least 20 samples per leaf were used to ensure adequate sample size for optimal performance. A Feature Sampling Ratio (FR) was utilized at 0.8. The decay factor λ was experimentally determined using a 30-day sliding window. It was determined to have an effective decay factor of 0.95. The configurations described above represent a compromise between prediction performance and resource efficiency, resulting in a consistent and reliable benchmark for comparative studies and ablation experiments.

To evaluate the system from an operational perspective, we conducted a deployment simulation using a lightweight service architecture. The system was evaluated with one hundred concurrent user sessions to measure real-time response latency and resource consumption. Additionally, a service outcome simulation was performed over a 90-day period, where the adaptive system was compared against a static scheduling baseline in terms of resource utilization efficiency (course seat occupancy) and service coverage (proportion of users receiving at least one recommended course per week). These system-level metrics complement the predictive accuracy evaluations and provide insight into the practical feasibility of deploying the proposed framework in real-world elderly education service operations.

3.2. Evaluation Indicators

To fully assess how well the course recommendation system performs, this research reviews four measures or indicator dimensions: user responses, subjective user satisfaction, ranking of the recommended course lists, and the coverage of course content provided by the recommendation system. A user's click rate for a course listed in his/her recommended courses is a measure of what percentage of that user's recommended courses are viewed/clicked on by him/her. This provides a direct reflection on the course recommendation system's surface-level attractiveness of the recommendations. The percentage of courses rated 4 stars or higher by users in the test set is used to measure user satisfaction with the recommended courses relative to other courses in the user's recommended course listings. The Normalized estimated cumulative gain is a measure of the overall ranking quality of the recommended list (Cai et al., 2022; Zheng and Wang, 2022), as explained below in Eq. (7).

$$NDCG@K = \frac{DCG@K}{IDCG@K}, \; DCG@K = \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{log_2(i+1)} \tag{7}$$

In Eq. (7), K denotes the length of the recommendation list in our study, it sets K=10 to reflect a realistic deployment scenario. The term rel_i indicates the actual relevance of the course at position i, typically encoded as 1 if the user clicked on it and 0 otherwise. The denominator, Ideal Discounted Cumulative Gain at K (IDCG@K), represents the best possible cumulative gain achievable if the recommendations were perfectly ordered by relevance. To assess course diversity, it computes the average cosine dissimilarity between all pairs of courses in the top-K list. This metric helps gauge how well the system avoids recommending overly similar content and instead offers users a varied and enriching set of options (Friedman and Bousso Dieng, 2022). For clarity, Table 3 compiles the definitions and corresponding formulas for all evaluation metrics used in this work.

Table 3. Evaluation indicators and calculation methods

Metric name	Definition	Calculation equation
Course click-through rate	Proportion of clicked courses in the recommendation list	$\mathrm{CTR} = \frac{\mathrm{N_{click}}}{\mathrm{N_{Impression}}}$
User satisfaction	Proportion of high-rating courses (Rating ≥ 4)	$\mathrm{Satisfaction} = \frac{\mathrm{N_{rating}} \geq 4}{\mathrm{N_{total\_rating}}}$
Normalized discounted cumulative gain	Normalized measure of ranking quality	$\mathrm{NDCG@K} = \frac{\mathrm{DCG@K}}{\mathrm{IDCG@K}}$
Course diversity	Average content dissimilarity in the recommendation list	$\mathrm{Diversity} = 1 - \frac{1}{\mathrm{K(K-1)}} \sum_{\mathrm{i \neq j}} \cos\,(\mathrm{v_i}, \mathrm{v_j})$

Through Table 3, the definitions and methods by which each evaluation indicator is defined mathematically and quantitatively are provided which in combination create a framework that provides an overall assessment of the performance of a recommendation system from various angles while ensuring that any and all results obtained can accurately depict the performance level of the course adaptation function to its true accuracy level.

4. Results and Analysis

4.1. Overall Model Performance Comparison Analysis

In this section, it aims to characterize the overall performance of the new dynamic course adaptation system created in this paper by reviewing the temporal augmentation LightGBM model against industry-leading recommendation systems in four specific areas: course click-through rate, user satisfaction, ranking quality, and diversity. To this end, it selects three representative benchmarks. That is, one for each type of collaborative filtering and one for latent semantic matrix factorization, neighborhood-based Collaborative Filtering (CF), matrix factorization using latent variables, and neural collaborative filtering. Each of these recommended models is used for personalized recommendations, but they typically do not model user interest evolution explicitly. A full comparison of the model's performance can be found in Fig. 2.

The performance of the model under comparison is presented in Fig. 2, where it has been plotted against the four metrics of comparison: Click-Through Rate (CTR), User Satisfaction, Normalized Discounted Cumulative Gain at 10 (NDCG@10), and course diversity. The proposed model achieves the highest performance when all four metrics are considered simultaneously, yielding a CTR of 0.328, a user satisfaction score of 0.426, and an NDCG score of 0.751, covering the largest area under the curve. This prominent level of performance results from the proposed model leveraging deep mining and extracting temporal dynamic features that account for changes in interest over time of the elderly users, thereby better satisfying the needs and long-term preferences of the elderly user population in terms of recommendation ranking. In contrast, the performance of collaborative filtering-inferencing models is extremely poor due to sparse data environments, yielding a CTR of 0.264 and a user satisfaction score of only 0.332, because they are heavily dependent on the density of the user-course interaction matrix. In addition, although the neural collaborative filtering model demonstrated a CTR of 0.301 and an NDCG@10 score of 0.723, thus performing better than any other compared methods, its deep learning architecture requires a minimum number of quality training samples, which prohibits it from fully reaching its potential on the relatively sparse elderly user behavioral data. The results of this study indicate that, compared to existing mainstream models, the proposed approach has a significantly better overall performance in the area of recommendation systems and offers a viable technical alternative to provide personalized education services to the elderly.

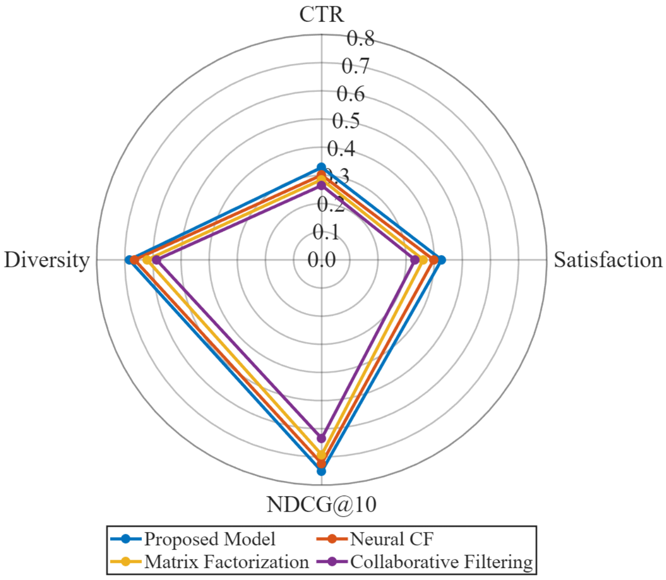


Fig.2. Overall performance comparison of recommendation models

4.2. Validity Analysis of Time Series Features

This section sets up an ablation study to quantify the impact of temporal dynamic features on model performance. It does so by developing a comparative model that includes only static features and comparing its performance with that of the full model, which includes temporal features, while keeping all other variables constant to eliminate bias, allowing the independent effectiveness of the temporal-feature module to be measured. The results from the comparison of both model's performance on the test set are illustrated in Fig. 3.

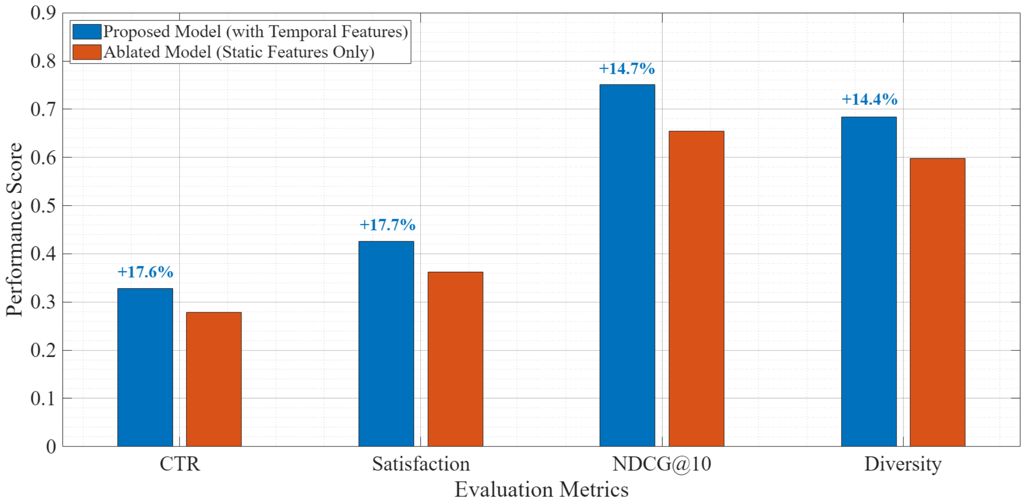


Fig. 3. Comparison of Time-series Feature Ablation

The outcome of the ablation study is summarized in Fig. 3, which contains the four evaluation metrics as the horizontal axis and the performance score of each metric as the vertical axis. The full model with temporal dynamics outperforms the static model on all metrics, with the greatest difference in user satisfaction, which improved by 17.7% (0.362 to 0.426) as compared to the static model. This improvement is directly attributable to the temporal dynamics capability of the model to define how older adult's interests change over time by providing up-to-date information on their rating preferences and the frequency of interaction through the use of a Sliding Window approach to analyze the changes in rating patterns and the frequency of interaction, which shows how rapidly the user's preferences are changing. Therefore, enabling the model to adapt its recommendations based on the rate of change. The NDCG@10 score increased from 0.655 to 0.751 (almost 14.7%), which indicates that temporal signals improve the ranking quality of the recommended courses and increase the likelihood of their being ranked highly in the recommendation list. Because this model was developed with more importance placed on more recent interactions, it provides recommendations based on what users are most interested in at any given time. The increase in the click-through rate from course to course was also convincing evidence (17.6%) that dynamic features were identifying those things that are now most desired by each user. Moreover, both results support the main conclusion that temporally driven data modelling can enable accurate and fast recommendation systems to be created for elderly users interested in learning to dance. By providing an explicit numerical representation of interest drift over time, the user can adjust the system to their current information needs.

4.3. Impact Analysis of Dynamic Update Mechanism

A longitudinal six-cycle study was designed to assess how effectively the dynamic update mechanism can accommodate drift in user's interests over an extended period of time. The goal of this study is to evaluate how well each model (e.g., the model with an online learning capability and the model that does not receive any updates) adapts when the interests of users change. The evaluation results are shown in Fig. 4, which plots the output of both models at each of the six update cycles.

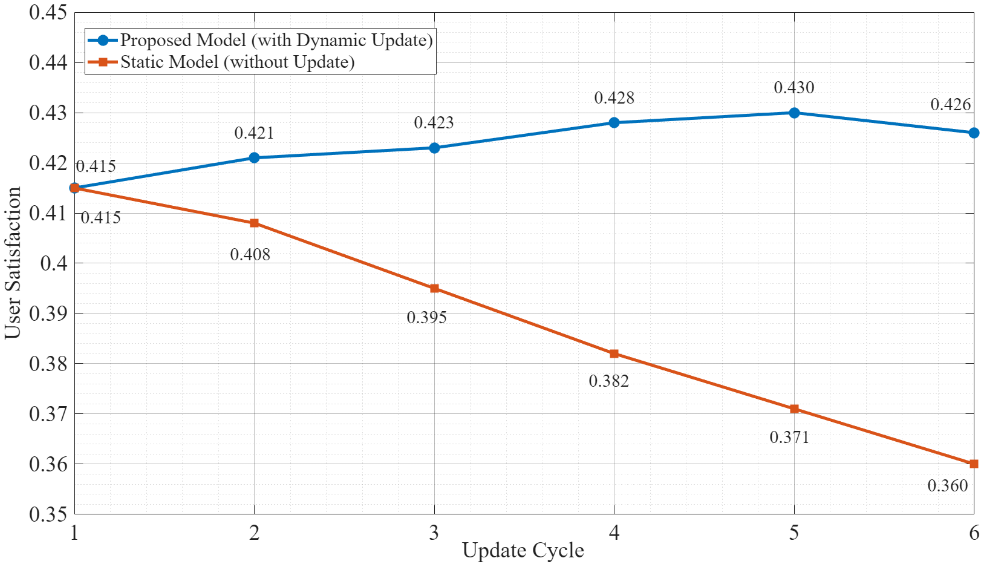


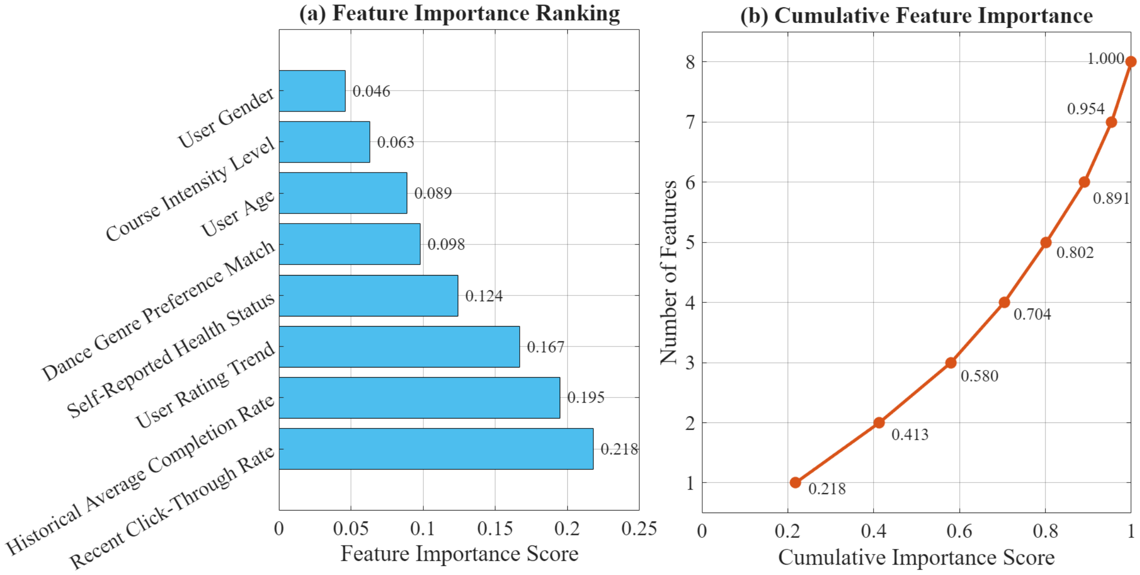
Fig. 4. Impact of dynamic update mechanisms on long-term performance

Model performance can be observed over time as shown in Fig. 4. The x-axis indicates six sequential updates, and the y-axis is user satisfaction. The dynamic method indicated continued growth in user satisfaction through an exponential decay process. Starting at 0.415 and reaching 0.426 through the sixth update cycle, with a consistent, gradual increase. This gradual improvement reflects the system's ability to continuously learn from fresh user interactions while still honoring past behavior through an exponential decay-based weighting scheme. The static method indicated continued loss of user satisfaction from the same starting point of 0.415 down to the sixth update cycle, which goes from 0.415 to 0.360, representing a 13.3% drop in user satisfaction. Since the static method does not adapt to the evolving preferences and behaviors of older populations, such as seasonality, progress in personal learning, and increased social engagement. By the sixth cycle, the performance gap between the two models has widened to 0.066, a meaningful difference that underscores just how critical ongoing adaptation is in a real-world recommendation setting. These findings confirm that the dynamic weight update mechanism acts as a vital feedback loop: by enabling continuous, incremental learning, it effectively counters the performance decay that inevitably plagues static systems in the face of evolving user preferences.

4.4. Feature Importance Analysis

It looks at the basic internal drives that influence how older adult users want to dance as part of this section's feature importance study using a trained LightGBM model. The study uses the cumulative contribution of information gain calculated during the splits of the decision trees created by the LightGBM classifier to determine how much each feature contributes to the final prediction of the model. Aggregating this information gains an overall ranking of the importance of each feature as input to the model, which demonstrates what drives how users decide to dance. A visual representation of the model's calculated feature importance rankings can be found in Fig. 5.

The contribution and explanation of each feature, along with their cumulative contribution, are shown in Fig. 5 for all features. The combination of the recent course click-through rate (0.218) and the historical average course completion rate (0.195) accounts for 41.3% of the total feature set's contribution, supporting the idea that temporally influenced user behavior provides the most accurate indication of the strength of interest. In addition, the user rating trend (0.167) indicates the importance of continually monitoring user feedback to capture their overall satisfaction level. Furthermore, the self-reported health status (0.124) shows how various physiological characteristics of older adults affect their engagement with the course. In Fig. 5(a), the cumulative curve shows that the first four features cover 70.4% of the model's decision information, while demographic features such as user age (0.089) and gender (0.046) contribute little, which suggests that dynamic relationship patterns are much more predictive than static attributes in predicting an older adult's course recommendation behavior. The distribution of feature importance further supports the role of dynamic attributes over time as being critical to creating a model of elder user preference.



(a) Feature Importance Ranking (b) Cumulative Feature Importance

Fig. 5. Feature importance ranking

4.5. System Deployment Simulation

Table 4 summarizes the operational performance of the dynamic course adaptation system under simulated deployment conditions. The average response time remained below 300ms under concurrent load, and CPU and memory usage stayed within acceptable ranges for typical edge server configurations. In the 90-day service simulation, the adaptive system achieved a resource utilization rate of 78.4%, significantly outperforming the static baseline (52.1%). Service coverage improved from 64.7% to 89.2%, indicating that the dynamic mechanism effectively allocates course resources to a broader user base. These results confirm that the proposed system not only improves predictive accuracy but also delivers tangible operational benefits suitable for real-world deployment.

Table 4. System deployment simulation results

Operational Metric	Static Baseline	Proposed System
Avg. Response Time (ms)	—	286
CPU Usage (%, peak)	—	42
Memory Usage (GB)	—	3.2
Resource Utilization (%)	52.1	78.4
Service Coverage (%)	64.7	89.2

5. Conclusion

This study successfully achieved accurate modeling and dynamic course adaptation of the elderly's dance interests and preferences by constructing a time-enhanced LightGBM model and combining it with a dynamic weight update mechanism. The method first extracts time-series features, such as sliding window statistics, from user behavior sequences to quantify interest drift. Then it uses the LightGBM framework to learn the complex mapping between features and preferences and finally achieves continuous model optimization via an online learning mechanism. Experimental results show that the system achieves excellent performance of 0.328, 0.426, and 0.751 in three key indicators: course click-through rate, user satisfaction, and NDCG@10, respectively. Ablation experiments further confirm that applying time-series features results in a 17.7% increase in user satisfaction. Feature importance analysis shows that recent click-through rate and historical course completion rate are the most influential predictors, verifying the core position of dynamic behavioral features in elderly preference modeling. The study provides an effective technical approach to address rapidly changing levels of interest in personalized services for the elderly. As such, the system framework developed through this research study can be valuable for deployment in practice and can therefore enhance the accuracy and adaptability of dance education services delivered to our aging population.

From a managerial perspective, this paper enables data-driven decisions: administrators can use the LightGBM model to dynamically tailor course offerings based on predicted interest, prioritize courses with higher engagement potential, and continuously update content using real-time user feedback. The emphasis on recent click-through and completion rates guides managers to focus on the most influential behavioral indicators, thereby improving resource allocation and learner satisfaction.

Beyond its immediate applications, this research invites reflection on several broader issues. First, it raises the question of whether recommendation systems should merely predict and adapt to existing interests or actively shape and expand them, introducing older adults to novel dance forms they might not have considered. This tension between "interest prediction" and "interest cultivation" challenges the passive logic of many personalized algorithms. Second, the dynamic modeling approach demonstrated here could be extended beyond dance education to other domains serving aging populations, such as personalized health interventions, social activity planning, or cognitive training programs. Third, and more critically, as such systems become increasingly predictive, we must remain mindful of the ethical boundaries between personalization and manipulation. The pursuit of engagement metrics should not overshadow the deeper goal of supporting autonomy, well-being, and genuine human flourishing in later life. These considerations point toward a future where adaptive technologies are designed not just to follow, but to respectfully accompany, the evolving preferences of older adults.

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Institutional Review Board Statement

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Declaration of Artificial Intelligence (AI) Tools

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Cui Yalin is a dance instructor at the School of Music, Taizhou University, China, and a Ph.D. candidate in Dance at Sookmyung Women's University, South Korea. She is a member of the Chinese Society of Ethnic Dance and the Taizhou Dancers Association. Her research interests include dance education, ethnic dance studies, and dance curriculum development. She has published several papers and participated in provincial and municipal research projects. She has received awards in several international dance competitions and has been invited to perform at international dance festivals.