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Article

Goal Aware Fine Grained Personalized Learning Framework Adaptive to Dynamic User Profile

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Abstract: Personalized e-learning platforms enhance the learning experience by adapting educational content according to learners' learning styles, knowledge levels, and affective states. In our previous work, a fine-grained learning style prediction framework was proposed that adapted to learner knowledge profiles, content semantics, and temporal affective states. However, the framework relied on coarse-grained interaction statistics to model learner preferences, limiting its ability to capture the temporal evolution of learner behavior during the learning process. Furthermore, the framework personalized learning resources solely based on learner characteristics without considering administrator-defined learning objectives. To address these limitations, this paper proposes a Goal-Aware Fine-Grained Personalized Learning Framework (GAFG-PLF) that jointly models content semantics, learner knowledge profiles, temporal affective states, dynamic interaction behavior, and administrator-defined learning goals. The proposed framework consists of two key components: (i) a **Dynamic Preference** Evolution Network, which continuously estimates evolving learner preferences using multimodal learning cues, and (ii) a Goal-Aware Recommendation Engine, which recommends the most appropriate learning resources by integrating predicted learning styles, dynamic learner preferences, knowledge profiles, affective states, and instructional objectives. Experimental evaluation demonstrates that the proposed framework significantly improves learning style prediction accuracy and enhances recommendation quality compared with existing approaches. These improvements contribute to a more adaptive, learner-centric, and goal-oriented personalized e-learning environment, thereby supporting better learning outcomes and more effective educational resource delivery.
Keywords: Personalized learning, Goal-aware recommendation, Affective computing, Learning analytics, Learning style prediction

1. Introduction

E-learning facilitates self paced, flexible and accessible learning experiences for learners. Different from conventional learning, the E-learning platforms can collect learner's interactions with digital learning resources and provide valuable information for personalizing the learning process [1,2]. The personalization in terms of adapting instructional strategies, content presentation, and learning pathways according to individual learner characteristics improves the learning effectiveness. Various personalized e-learning systems have been proposed [3-5] which personalizes the learning process using the information gathered from user interaction with learning systems. These approaches predict the learning style, affective state and knowledge level from user interaction and based on it recommends/personalizes the contents. Learning style prediction is an important component of personalized e-learning systems. Learning style prediction techniques collects the interaction information in a non intrusive manner and applies machine learning techniques to predict the user learning styles. Recent advances in artificial intelligence, deep learning, and learning analytics have significantly improved the ability of adaptive learning systems to model learner knowledge, affective states, and behavioral interactions. Several researchers have proposed learning style prediction models based on learner interaction sequences, knowledge profiles, engagement analysis, facial emotion recognition, and multimodal data fusion. In our earlier work, a fine-grained learning style prediction [6] based on joint analysis of content semantics, user knowledge profile and temporal affective state was proposed. This fine-grained prediction provided more flexibility in personalizing the course delivery mode specific to course semantics, user mental state and user knowledge level. This method improved the accuracy of learning style prediction. But this method had two open issues. Though the method captured dynamic interactions with contents, it could not model evolving user preferences and learning styles. Also it lacked content recommendation component adaptive to predicted learning styles and administrator-defined learning objectives. These limit its applicability in real educational environments where learning must satisfy both learner preferences and institutional goals. Addressing these two open issues, this work proposes a Goal-Aware Fine-Grained Personalized Learning Framework (GAFG-PLF). The proposed framework has a a Dynamic Preference Evolution Network (DPEN) that continuously models learner preferences from fine-grained behavioral interactions, including navigation patterns, content revisits, video engagement, assessment behavior, and temporal learning dynamics addressing the first issue. It has a Goal-Aware Recommendation Engine (GARE) integrating administrator-defined learning objectives with learner knowledge, affective state, dynamic preferences, learning styles, and content semantics to generate personalized content recommendations and adaptive learning pathways to address the second issue. With the use of both DEPN and GARE, the proposed solution performs multi-objective optimization to simultaneously maximize learning effectiveness, learner engagement, knowledge mastery, and administrator learning objectives. Following are the contribution of GAFG-PLF

(i) A novel Dynamic Preference Evolution Network (DPEN) is proposed to continuously model fine-grained learner interaction behaviors and temporal preference evolution during the learning process. The interaction behavior is integrated with learner knowledge profile, content semantics and temporal affective state to predict the learning styles.

(ii) A Goal-Aware Recommendation Engine (GARE) is proposed to integrate administrator-defined learning objectives into personalized content recommendation and adaptive learning path generation. This optimizes learner engagement, learning effectiveness, knowledge acquisition, and curriculum goal attainment jointly.

The rest of the sections in paper are organized as follows. Section II presents the literature survey on learning style prediction and content recommendation techniques. Section III presents the proposed GAFG-PLF. Section IV presents the experiments and results of the proposed GAFG-PLF. Section V presents the concluding remarks and future scope of work.

2. Literature Review

The existing literature was reviewed in two major areas: learning style prediction and personalized recommendation systems.

2.1 Learning Style Prediction

Altamimi et al. [7] proposed a regression-based framework for predicting learners' VARK learning styles, enabling probabilistic estimation of multiple learning preferences instead of assigning a single dominant learning style. Although the approach improved prediction flexibility, it relied on questionnaire-based responses, making the prediction process intrusive. Alshmrany et al. [8] developed a convolutional neural network (CNN)-based framework for automatic learning style prediction using learner activity logs. While the framework achieved high prediction accuracy, it utilized only coarse-grained interaction statistics and did not consider content semantics or temporal preference evolution. Bello et al. [9] employed a graph neural network to predict learning styles based on learner interactions. However, the model relied mainly on aggregate interaction features and ignored learners' affective states and dynamic behavioral changes.

Pardamean et al. [10] developed an AI-based learning style prediction framework and recommended course materials using collaborative filtering and learner ratings. However, the dependence on explicit learner feedback limited its applicability in fully automated adaptive learning environments. Lokare and Jadhav [11] proposed an AI-based personalized learning framework using attention level, meditation, cognitive workload, facial expressions, and emotional states. Nevertheless, the framework did not consider learner knowledge profiles or course semantic information. Hussain et al. [12] introduced a hybrid deep learning framework combining Long Short-Term Memory (LSTM) networks with sentiment analysis to identify learners' learning styles. Although the framework achieved improved prediction performance, it relied on explicit questionnaires and lacked fine-grained behavioral interaction modeling.

Aly et al. [13] detected learners' emotions from facial videos and adapted course content accordingly. However, the approach considered only visual affective cues without incorporating learner interaction behavior, knowledge progression, or course characteristics. Gupta et al. [14] predicted learner engagement using facial emotion recognition and adapted course content based on the detected emotions. Nevertheless, the framework ignored learning preferences, course semantics, and temporal interaction patterns. Rathi et al. [15] predicted learners' affective states using multimodal behavioral data. Although the proposed model accurately identified affective states, it did not utilize them for learning style prediction or personalized course recommendation.

The literature indicates that most existing learning style prediction approaches rely on static learner profiles or coarse-grained interaction features. Moreover, they rarely capture the temporal evolution of learner preferences and generally ignore the combined influence of content semantics, learner knowledge, dynamic interaction behavior, affective states, and administrator-defined instructional objectives.

2.2 Recommendation

Zhang et al. [16] proposed a neural time-aware sequential recommendation model that captured users' long-term preferences and short-term behavioral dynamics using temporal interaction sequences. Although the model achieved high recommendation accuracy, it did not consider learner characteristics, learning styles, or educational objectives. Xiao et al. [17] developed a graph neural network-based recommendation framework in which users' long-term and short-term preferences were represented as graphs to predict user-item preferences. However, the framework did not incorporate learner knowledge, affective states, or pedagogical learning goals.

Alabduljabbar et al. [18] presented a comprehensive survey of time-aware recommender systems that exploit temporal information to model evolving user interests. The authors concluded that temporal modeling improves recommendation performance but observed that most educational recommender systems rarely integrate instructional goals or learner-specific cognitive characteristics. Deng et al. [19] proposed a graph-guided session-based recommendation model that captured both global and local user navigation patterns for next-item recommendation. However, the model focused only on session behavior and did not support adaptive learning or educational content personalization. Zhang et al. [20] introduced a graph neural network-based recommendation framework integrating temporal session information with graph-based user-item relationships. Although recommendation accuracy improved through temporal dependency modeling, the solution did not consider learner emotions, knowledge progression, or adaptive learning objectives. Deldjoo et al. [21] explored techniques for improving fairness, transparency, and user trust in recommender systems. However, the proposed techniques were not specifically designed for adaptive educational environments and did not provide goal-oriented personalized learning recommendations.

The literature review shows that existing recommendation systems primarily optimize user preferences and recommendation accuracy while overlooking educational factors such as learner knowledge, learning styles, affective states, and administrator-defined instructional objectives. Furthermore, most existing methods do not model the dynamic evolution of learner preferences or incorporate pedagogical goals, thereby limiting the effectiveness of personalized learning recommendations.

3. Materials and Methods

3.1 Proposed System

The architecture of the proposed GAFG-PLF is given in Figure 1. GAFG-PLF extends the core idea of joint analysis of content/course semantics, user knowledge level and temporal affective state proposed in our earlier work [6]. GAFG-PLF has two important functional components (a) dynamic preference evolution network and (b) goal aware recommendation engine. In the dynamic preference evolution network, the course curriculum is represented as a directed knowledge graph in which each node corresponds to a learning module and edges represent prerequisite relationships. From the graph, the critical learner assessment point called Joint Analysis Points (JAPs) is determined. At every JAP, learner knowledge profile, content semantics, affective state, interaction behavior and dynamic preferences are jointly analyzed to estimate the time varying learner's learning style. From predicted learning styles and administrator defined learning objectives, the goal aware recommendation engine provides the most appropriate learning resources and adaptive learning paths. Each of these functional components is detailed in below subsections.

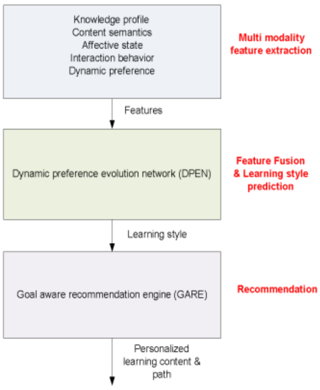

Figure 1 Architecture of GAFG-PLF

3.2 Multimodal feature extraction

The learning curriculum is modeled as graph $G(V, E)$ with each node (V) representing a learning module and edge (E) representing the prerequisite requirement between the modules. The learner evaluation point JAP is found on the graph using the Steiner minimal tree based approach proposed in [6]. At each of the JAP a multimodal feature composing of features in modalities of knowledge profile, content semantics, affective states, interaction behavior and dynamic preference vector are collected. The features are summarized in Table 1.

Table 1 Multimodal feature

Modality	**Feature**	**Description**
Knowledge profile	Quiz score, Assignment score, Assessment accuracy, Concept mastery level, Previous learning history, Knowledge gain	Estimates the learner's cognitive understanding and current knowledge level.
Content Semantics	Topic embedding, Concept similarity, Difficulty level, Learning resource type (video/text/quiz), Keyword embedding, Concept dependency	Represents semantic characteristics of learning resources for adaptive matching
Affective state	Happy, Neutral, Confused, Frustrated, Bored, Engaged, Attention level	Measures learner emotions and engagement during learning sessions
interaction behavior	Learning duration, Click frequency, Number of attempts, Navigation path, Mouse movements, Page transitions	Captures learner interactions with the e-learning platform
Dynamic Preference	Video replay count, Pause frequency, Skip rate, Scroll speed, Content revisit count, Response latency, Playback speed, Preferred content type	Models evolving learner preferences and behavioral changes over time.

3.3 DPEN

The proposed **Dynamic Preference Evolution Network (DPEN)** is designed to capture the fine-grained temporal evolution of learner preferences from multimodal interaction data. Conventional learning style prediction approaches generally rely on aggregated interaction statistics, which fail to represent the continuous changes in learner behaviour during the learning process. In contrast, DPEN models learner behaviour as a chronological sequence of interaction events and continuously updates learner preferences by considering content difficulty, prior knowledge, emotional state, cognitive load, and behavioural interactions. The framework consists of three major components: **Behavior Encoder**, **Session Encoder**, and **Preference Summarizer**, which collectively generate an evolving learner preference representation for accurate learning style prediction.

Initially, the interaction events collected during a learning session are represented as an ordered sequence

$$E = \{e_1, e_2, e_3, \dots, e_n\} \quad (1)$$

where e_i denotes the i^{th} learner interaction event.

Each interaction event is represented by multiple behavioural attributes as

$$e_i = \{t_i, b_i, r_i, d_i, m_i, k_i\} \quad (2)$$

where $t_i$represents the timestamp, $b_i$denotes the interaction behaviour (pause, replay, skip, scroll, click, etc.), $r_i$represents the learning resource type, $d_i$denotes the content difficulty level, $m_i$indicates the learner's emotional state, and $k_i$represents the learner's knowledge level.

The **Behavior Encoder** transforms every interaction event into a dense vector representation by combining event embeddings with positional and temporal encodings. The event embedding is computed as

$$x_i = Emb(e_i) + PE_i + TE_i \quad (3)$$

where $Emb(e_i)$denotes the event embedding, PE_irepresents the positional encoding, and TE_idenotes the temporal encoding that preserves the time interval between consecutive learning events.

The embedded interaction sequence is represented as

$$X = \{x_1, x_2, \dots, x_n\} \quad (4)$$

The sequence is processed by a Transformer encoder to capture contextual relationships among learner interactions.

$$H = Transformer(X) \quad (5)$$

where

$$H = \{h_1, h_2, \dots, h_n\} \quad (6)$$

represents the contextual feature representations generated by the Transformer.

To identify the most informative behavioural events, DPEN employs a **multi-head self-attention mechanism** defined as

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (7)$$

where Q, K, and Vdenote the query, key, and value matrices, respectively, and $d_k$represents the dimensionality of the key vectors.

Multiple attention heads are combined to learn diverse behavioural representations as

$$MH(H) = Concat(head_1, \dots, head_h)W^O \quad (8)$$

where $head_i$represents the output of the i^{th}attention head and W^Odenotes the output projection matrix.

The encoded interaction features are then aggregated by the **Session Encoder**, which summarizes the learner behaviour observed within an individual learning session. The session representation is computed as

$$S_r = \frac{1}{m}\sum_{i=1}^{m} H_i \quad (9)$$

where $m$denotes the total number of interaction events in the session.

To capture long-term instructional preferences, the **Preference Summarizer** maintains a dynamic preference memory that is continuously updated after every learning session using

$$M_t = \alpha M_{t-1} + (1-\alpha)S_r \quad (10)$$

where $M_t$denotes the updated preference memory, M_{t-1}represents the previous memory state, $S_r$is the current session representation, and $\alpha$is the forgetting factor controlling the contribution of historical and recent learner behaviours.

The final learner preference representation is obtained as

$$P_t = f(M_t) \quad (11)$$

where $f(\cdot)$denotes the preference transformation function that generates the evolving learner preference vector.

The proposed framework further integrates learner knowledge, course semantics, affective state, interaction behaviour, and evolving learner preferences using a **Cross-Modal Attention Fusion (CMAF)** module. The fused feature representation is computed as

$$F = CMAF(K, C, A, I, P) \quad (12)$$

where K, C, A, I, and Prepresent learner knowledge, course semantic information, affective state, interaction behaviour, and learner preference representation, respectively. The CMAF module assigns adaptive attention weights to each modality and produces a unified feature representation that preserves both intra-modal and inter-modal relationships.

The fused feature vector is finally provided as input to a **Random Forest (RF)** classifier for learning style prediction. The predicted learning style is obtained as

$$\hat{Y} = RF(F) \quad (13)$$

where

$$\hat{Y} \in \{Visual,\ Auditory,\ Read/Write,\ Kinesthetic\}$$

represents the four VARK learning style categories.

The final learning style prediction is determined using majority voting among all decision trees in the Random Forest classifier as

$$\hat{y} = mode(T_1(F), T_2(F), \dots, T_N(F)) \quad (14)$$

where $T_i(F)$denotes the prediction generated by the i^{th}decision tree. The predicted learning style is subsequently forwarded to the **Goal-Aware Recommendation Engine (GARE)** for personalized learning resource recommendation.

The implementation parameters of the proposed DPEN, including embedding dimension, positional encoding, Transformer configuration, attention heads, hidden dimension, learning rate, batch size, optimizer, and training epochs, are summarized in **Table 2**.

Table 2 DPEN configuration

Parameter	**Value**
Embedding Layer	Embedding dimension = 128
Positional Encoding	Sinusoidal positional encoding
Temporal Encoding	Relative time interval encoding
Behavior Encoder	Transformer Encoder
Number of Transformer Layers	4
Number of Attention Heads	8
Hidden Dimension	256
Activation Function	GELU
Dropout Rate	0.2
Session Encoder	Mean Pooling
Preference summarizer	Exponential Moving Average
Preference Update Factor (α)	0.8
Output Dimension	128
Optimizer	Adam
Learning Rate	0.001
Batch Size	32

Loss Function	Cross entropy loss
Training Epochs	100

3.4 Goal-Aware Recommendation Engine (GARE)

The Goal-Aware Recommendation Engine (GARE) generates personalized learning resource recommendations by jointly considering the learner's predicted learning style, knowledge profile, dynamic preferences, affective state, course semantics, and administrator-defined instructional objectives. Unlike conventional recommender systems that primarily optimize user preferences or historical interactions, the proposed GARE incorporates pedagogical goals into the recommendation process to ensure that the recommended learning resources satisfy both learner requirements and course objectives.

Initially, the administrator specifies one or more instructional goals before the learning process begins. These goals may include examination preparation, competency development, weak-topic reinforcement, learner engagement enhancement, or course completion. The specified goals are encoded into a learning objective vector, which is subsequently integrated with learner-specific information during recommendation generation.

The recommendation problem is formulated as a multi-objective optimization problem, where every candidate learning resource is evaluated according to six complementary objective functions. These objective functions measure learning style compatibility, dynamic preference similarity, learner knowledge suitability, affective state compatibility, semantic similarity, and goal satisfaction. Each objective value is normalized to the range [0,1], and a composite recommendation score is computed by assigning suitable importance weights to every objective.

Table 3 GARE objective functions

Objective score	**Description**
$f_1(r_i)$	Learning style compatibility: Computes the similarity between the learner's predicted VARK learning style and the instructional style of the candidate learning resource. A score of 1 indicates a perfect match, while 0 indicates no compatibility.
$f_2(r_i)$	Dynamic preference similarity: Computes the cosine similarity between the learner's dynamic preference vector generated by DPEN and the behavioral characteristics of the candidate resource (e.g., video, text, simulation, quiz).
$f_3(r_i)$	Knowledge suitability: Measures the compatibility between the learner's current knowledge level and the estimated difficulty level of the learning resource. Resources whose difficulty closely matches the learner's mastery receive higher scores.
$f_4(r_i)$	Affective compatibility: Evaluates whether the candidate resource is appropriate for the learner's current emotional state. For example, learners identified as confused may receive explanatory videos or worked examples instead of advanced assessments.
$f_5(r_i)$	Semantic similarity: Computes the cosine similarity between the semantic embedding of the learner's current learning concept and the semantic embedding of the candidate resource using transformer-generated embeddings
$f_6(r_i)$	Goal vector satisfaction factor: Measures how well the learning resource satisfies administrator-defined instructional goals such as examination preparation, competency mastery, weak-topic reinforcement, learner engagement, or course completion

The first objective evaluates the compatibility between the learner's predicted VARK learning style and the instructional style of the candidate learning resource.

$$f_1(r_i)$$

This objective computes the similarity between the learner's predicted learning style and the instructional characteristics of the candidate resource. A value close to 1 indicates high compatibility, whereas a value close to 0 indicates poor compatibility.

The second objective measures the similarity between the learner's evolving preference representation generated by the Dynamic Preference Evolution Network (DPEN) and the behavioural characteristics of the candidate learning resource.

$$f_2(r_i)$$

This objective enables the recommendation engine to adapt continuously to changes in learner preferences observed during the learning process.

The third objective evaluates the suitability of a learning resource according to the learner's current knowledge level.

$$f_3(r_i)$$

Resources whose difficulty level closely matches the learner's knowledge profile receive higher scores, thereby reducing cognitive overload while encouraging gradual knowledge progression.

The fourth objective measures the compatibility between the learner's current affective state and the learning resource.

$$f_4(r_i)$$

For example, learners experiencing confusion or frustration may receive explanatory videos or worked examples instead of complex assessments, whereas highly engaged learners may receive more challenging learning activities.

The fifth objective evaluates the semantic similarity between the learner's current learning concept and the educational content of the candidate resource.

$$f_5(r_i)$$

Semantic similarity is computed using Transformer-generated embeddings, allowing conceptually relevant learning materials to be recommended even when explicit behavioural similarities are unavailable.

The sixth objective measures the extent to which the candidate learning resource satisfies the administrator-defined instructional goals.

$$f_6(r_i)$$

Resources that better satisfy objectives such as examination preparation, competency mastery, weak-topic reinforcement, learner engagement, or course completion receive higher recommendation scores.

After evaluating all six objective functions, the overall recommendation score for every candidate learning resource is computed using a weighted aggregation function.

$$Score(r_i) = \sum_{j=1}^{6} w_j f_j(r_i) \quad (15)$$

where $w_j$represents the weight assigned to the j^{th}objective function, satisfying

$$\sum_{j=1}^{6} w_j = 1.$$

The weighting coefficients reflect the relative importance of each recommendation objective and enable flexible adaptation to different educational requirements.

The candidate learning resources are ranked according to their composite recommendation scores, and the Top-K highest-ranked resources are recommended to the learner.

After every Joint Analysis Point (JAP), the learner profile is updated to reflect newly observed learning behaviour, knowledge acquisition, emotional state, and interaction patterns. The learner profile is updated as

$$L_{t+1} = L_t + \Delta(K, P, A, I) \quad (16)$$

where $L_t$denotes the current learner profile, $\Delta(\cdot)$represents the newly observed learner information, Kdenotes learner knowledge, Prepresents evolving learner preferences, Acorresponds to the learner's affective state, and Idenotes interaction behaviour. This adaptive profile updating mechanism enables continuous personalization throughout the learning process.

The overall workflow of the proposed GARE begins by constructing the course knowledge graph and identifying Joint Analysis Points (JAPs). At each JAP, learner knowledge, content semantics, affective state, interaction features, and fine-grained behavioural events are extracted. The extracted behavioural events are processed by the Dynamic Preference Evolution Network (DPEN) to generate an evolving learner preference representation. Subsequently, the multimodal learner features are integrated through the Cross-

Modal Attention Fusion (CMAF) module, and the fused representation is used by the Random Forest classifier to predict the learner's VARK learning style. Finally, the Goal-Aware Recommendation Engine evaluates all candidate learning resources using the six objective functions, computes their composite recommendation scores, ranks the resources, and recommends the Top-K learning resources that best satisfy both learner characteristics and administrator-defined instructional goals.

The implementation details of the six objective functions used by the proposed Goal-Aware Recommendation Engine are summarized in Table 2, while the complete workflow of the proposed framework is presented in Algorithm 1.

4. Results

The performance of the proposed Goal-Aware Fine-Grained Personalized Learning Framework (GAFG-PLF) was evaluated using the MUTLA dataset through 5-fold cross-validation. The framework was assessed for learning style prediction and personalized recommendation using standard classification and recommendation metrics. The performance was compared with existing state-of-the-art methods to demonstrate the effectiveness of the proposed approach.

Table 4: Five fold cross validation results

Fold	Accuracy	Precision	Recall	F1-score	CK	MCC
1	93.12	92.85	92.64	92.74	0.907	0.909
2	94.05	93.76	93.58	93.67	0.919	0.920
3	93.48	93.11	92.97	93.04	0.912	0.913
4	94.36	94.02	93.84	93.93	0.923	0.925
5	93.81	93.47	93.22	93.34	0.916	0.917
Mean ± SD	93.76 ± 0.49	93.44 ± 0.48	93.25 ± 0.49	93.34 ± 0.47	0.915 ± 0.006	0.917 ± 0.006

The comparison of performance with fine grained prediction model [6] is given in Table 5.

Table 5: Comparison

Parameters	Fine grained prediction model [6]	Proposed GAFG-PLF	% improvement
Accuracy	90.84	93.76	+2.92
Precision	90.21	93.44	+3.23
Recall	89.94	93.25	+3.31
F1-score	90.07	93.34	+3.27
CK	0.876	0.915	0.039
MCC	0.878	0.917	0.039

The proposed GAFG-PLF has consistent performance across all five folds of cross-validation, demonstrating its robustness and generalization capability. The proposed solution has higher performance compared to [6] across all the evaluation metrics. The improved performance in the proposed GAFG-PLF is due to integration of the Hierarchical Behavior-Aware Temporal Transformer-based Dynamic Preference Evolution Network, which captures evolving learner behaviors, and the Cross-Modal Attention Fusion mechanism, which effectively combines heterogeneous learner information before classification.

The ROC values are reported using a one-vs-rest (OvR) strategy, with the Area Under the Curve (AUC) for each class and macro/micro averages in Table 6.

Table 6: Comparison of ROC

Learning style	AUC
Visual (V)	0.973

Auditory (A)	0.965
Read/Write (R)	0.969
Kinesthetic (K)	0.978
Macro Average	0.971
Micro Average	0.972

The proposed GAFG-PLF achieved high AUC values for all four learning style classes, indicating excellent classification performance. The macro-average and micro-average AUC values of 0.971 and 0.972 demonstrate that the proposed framework consistently distinguishes among different learning style categories. These results indicate that the integration of the Dynamic Preference Evolution Network and Cross-Modal Attention Fusion produces highly discriminative multimodal representations for VARK learning style prediction

The recommendation effectiveness of the proposed GAFG-PLF is measured in terms of following metrics: Precision@5, Recall@5, Normalized discounted cumulative gain (NDCG@5), Mean average precision (MAP@5), Hit ratio@5. These metrics are calculated as follows

$$Precision@5 = \frac{No\ of\ relevant\ items\ in\ top\ 5}{5} \quad (17)$$

$$Recall@5 = \frac{No\ of\ relevant\ items\ in\ top\ 5}{Total\ relevant\ items} \quad (18)$$

$$NDCG@5 = \sum \frac{rel_i}{log_2(i+1)} \quad (19)$$

MAP@5 is the mean of the average precision values computed at the top-5 ranked recommendations for each user.

$$Hit\ ratio@5 = \{1, if\ atleast\ one\ relevant\ item\ in\ top\ 5\ 0, otherwise \quad (20)$$

This value is then averaged over users.

Recommendation performance of proposed GAFG-PLF against three recent educational recommendation systems Ren et al [23], Madhavi et al [24] and Zhang et al [25]. The feature wise comparison of these works is given in Table 8.

Table 7 Factor wise comparison

Factors	**Ren et al [23]**	**Madhavi et al [24]**	**Zhang et al [25]**	**Proposed GAFG-PLF**
Learning Style	✓	✗	✗	✓
Dynamic Preference	✗	✗	✓	✓
Multimodal	✓	✓	✓	✓
Goal-Aware	✗	✗	✗	✓
Sequential	✗	✗	✓	✓
Fine-Grained Behavior	✗	✗	Partial	✓

The comparison of recommendation results across the solutions is given in Table 8.

Table 8 Comparison of recommendation results

Metrics	**Ren et al [23]**	**Madhavi et al [24]**	**Zhang et al [25]**	**Proposed GAFG-PLF**
Precision@5	0.832	0.847	0.874	0.918
Recall@5	0.801	0.816	0.849	0.896

MAP@5	0.816	0.831	0.863	0.911
NDCG@5	0.841	0.856	0.888	0.931
Hit Ratio@5	0.914	0.927	0.951	0.981

The proposed GAFG-PLF provided better performance compared to the baseline methods. It has higher retrieval accuracy (Precision@5, Recall@5), better ranking effectiveness (MAP@5, NDCG@5) and stronger recommendation reliability (Hit Ratio@5). The recommendation quality improved in the proposed solution due to integration of evolving learning styles, course semantics, knowledge level and learners preference.

5. Discussion

The results show that the proposed GAFG-PLF improves both learning style prediction and personalized recommendation performance. Different from the existing systems which depend mainly on static learner profiles or coarse-grained interaction statistics, the proposed GAFG-PLF continuously models the evolution of learner behavior by integrating dynamic preferences, multimodal learner characteristics, and administrator-defined instructional objectives. This holistic representation enables the proposed solution to generate more accurate learner models and consequently improve recommendation quality.

Compared with the previously proposed fine-grained learning style prediction framework [6], GAFG-PLF achieves improvements across all evaluation metrics. The solution proposed in [6] estimated learning styles using multimodal learner information but did not explicitly model temporal preference evolution. In contrast, the proposed Dynamic Preference Evolution Network (DPEN) continuously updates learner preferences using fine-grained behavioral events such as video replay frequency, navigation patterns, scrolling behavior, response latency, and assessment interactions. The Hierarchical Behavior-Aware Temporal Transformer captures both short-term behavioral changes and long-term learning trends, allowing GAFG-PLF to adapt its learner representation throughout the learning process rather than relying on static interaction summaries.

Another major factor for the improved prediction performance is the Cross-Modal Attention Fusion (CMAF) mechanism. Traditional multimodal fusion methods generally concatenate heterogeneous features or assign fixed weights to different modalities, thereby ignoring their contextual dependencies. CMAF dynamically learns the relationships among learner knowledge, content semantics, affective state, interaction behavior, and dynamic preferences, assigning higher importance to the most informative modalities at each learning stage. Consequently, the generated multimodal representation contains richer contextual information, leading to more discriminative learning style prediction.

The factor-wise comparison with recent recommendation systems also explains the observed performance gains. GAFG-PLF is the only framework that simultaneously incorporates learning style prediction, dynamic preference modeling, multimodal information fusion, goal-aware optimization, sequential behavioral learning, and fine-grained interaction analysis. These complementary capabilities enable the framework to adapt continuously to learner progression while satisfying curriculum-level educational objectives, which are generally, overlooked in existing personalized recommendation systems.

Limitations: The experimental evaluation was conducted only using the MUTLA dataset, and additional validation on larger and more diverse educational datasets would further establish the robustness and generalizability of the framework. In addition, the administrator-defined objective weights used during recommendation are predetermined and remain fixed throughout training. Future work may investigate reinforcement learning or adaptive optimization techniques to automatically adjust these weights based on learner progress and instructional outcomes.

6. Conclusion

This work proposed a Goal-Aware Fine-Grained Personalized Learning Framework (GAFG-PLF) to dynamically adapt the e-learning process by integrating multiple learner- and content-related factors. Unlike conventional personalized learning approaches that rely on static learner profiles or coarse-grained interaction statistics, the proposed framework captures the continuous evolution of learner behavior through multimodal information, including learner interactions, knowledge profiles, affective states, and course semantics. A deep learning-based Dynamic Preference Evolution Network (DPEN) was developed to model the temporal changes in learners' preferences and learning styles throughout the learning process. Furthermore, the predicted dynamic learning styles were combined with course semantics, learner knowledge levels, and administrator-defined learning objectives to generate personalized learning recommendations that align with both individual learner needs and instructional goals.

The experimental evaluation demonstrates that the proposed framework achieves higher learning style prediction accuracy and improved recommendation quality when compared with existing personalized learning approaches. By incorporating dynamic learner behavior and goal-aware recommendation strategies, the framework effectively addresses the limitations of traditional adaptive learning systems that overlook temporal behavioral changes and predefined educational objectives. The results indicate that GAFG-PLF enhances learner engagement, supports more effective knowledge acquisition, and delivers a more adaptive and learner-centric educational experience.

Future work will focus on validating the proposed framework using large-scale real-world educational datasets and incorporating additional multimodal signals, such as eye-tracking data, speech analysis, and physiological indicators, to further improve the accuracy of learning style prediction and recommendation performance. In addition, future research will investigate the integration of explainable artificial intelligence techniques to provide transparent and interpretable recommendations, thereby increasing learner trust and supporting informed educational decision-making.

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