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Research on Constructing Personalized Learner Profiles Based on Multi-Feature Fusion

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Abstract: This study proposes a learner profile framework based on multi-feature fusion, aiming to enhance the precision of personalized learning recommendations by integrating learners' static attributes (e.g., demographic data and historical academic performance) with dynamic behavioral patterns (e.g., real-time interactions and evolving interests over time). The research employs Term Frequency-Inverse Document Frequency (TF-IDF) for semantic feature extraction, integrates the Analytic Hierarchy Process (AHP) for feature weighting, and introduces a time decay function inspired by Newton's law of cooling to dynamically model changes in learners' interests. Empirical results demonstrate that this framework effectively captures the dynamic evolution of learners' behaviors and provides context-aware learning resource recommendations. The study introduces a novel paradigm for learner modeling in educational technology, combining methodological innovation with a scalable technical architecture, thereby laying a foundation for the development of adaptive learning systems.

Keywords: Learner profile; Multi-feature fusion; Dynamic features; Personalized recommendation; Educational technology

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1. Introduction

1.1. Research background

With the rapid advancement of the Internet and digital technologies, online learning platforms have gained widespread popularity, enabling learners to access vast educational resources anytime, anywhere. However, this abundance of resources also poses challenges: learners often face information overload when attempting to identify content tailored to their specific needs. Amid the growing demand for personalized learning, efficiently matching resources to learners' requirements has emerged as a critical issue in educational technology.

Learner profiling, an extension of user profiling in the educational domain, involves analyzing learners' behaviors, interests, and habits to construct individualized models that support precise educational services.

Leveraging these profiles, personalized learning plans, resource recommendations, and tutoring can be delivered, thereby enhancing learning efficiency and experience. Nevertheless, existing research predominantly focuses on static features–such as age and academic grades–while overlooking the dynamic nature of learners' interests and behaviors. This limitation hampers the ability of profile models to adapt to real-time shifts in learning needs.

1.2. Research questions and objectives

Current learner profile studies tend to emphasize the extraction and analysis of static features, neglecting the dynamic changes in learners' interests and behaviors. Moreover, existing methods lack systematic and flexible approaches to feature extraction and weighting, making it difficult to adapt to diverse learning contexts and demands. This study addresses the following core research questions:

(1) How can learners' static attributes and dynamic behavioral patterns be integrated to construct accurate learner profiles?

(2) How can a dynamic feature update mechanism be designed to adaptively capture real-time changes in learners' interests?

(3) How can the effectiveness and practical value of this profile framework be validated in the context of personalized learning recommendations?

To tackle these questions, this research proposes a multi-feature fusion learner profile framework that combines static and dynamic features using TF-IDF, AHP, and a time decay function. The framework aims to create precise, real-time learner models, offering technical support for adaptive learning systems. Compared to traditional approaches, it not only accounts for persistent characteristics but also dynamically tracks interest evolution, injecting fresh vitality into personalized education.

2. Related work

2.1. Research on learner profiles

Learner profiling is an extension of user profiling techniques to the educational domain, aiming to construct personalized models by collecting and analyzing multidimensional data about learners. These models reflect learners' current states and predict their future learning trajectories, thereby supporting personalized instruction and resource recommendations. Existing research has explored the construction and application of learner profiles from various perspectives. For instance, Xiao *et al*. developed high-risk learner profiles for online learners based on basic characteristics, online learning behaviors, and learning pathways, using tags to identify potential dropout risks [1]. Wang *et al*. employed a bidirectional long short-term memory network (Bi-LSTM) with an attention mechanism for sentiment analysis, constructing learner profiles that include basic information, behavioral patterns, and textual interactions to predict potential learning needs [2]. These studies highlight the potential of profiling technology in education but often focus on static feature analysis, with less attention to the dynamic changes in learners' interests and behaviors.

2.2. Technologies related to user profiling

Before the advent of deep learning, user profiling relied heavily on traditional techniques such as regression analysis, clustering, and predictive modeling. For example, Schroeder *et al*. used k-means clustering to study the impact of group membership on learning transfer test scores [3], while Piech *et al*. applied recurrent neural networks (RNNs) to predict learners' cognitive levels [4]. In terms of visualization, methods like statistical mapping, text visualization, and human-computer interaction were widely adopted [5]. With the development of big data and artificial intelligence, capabilities for data processing and analysis have significantly improved, enabling more refined user profiles. Shao *et al*. proposed a user profile generation method based on multi-granularity information fusion (UP-MGIF), integrating bidirectional gated recurrent units (Bi-GRU), denoising autoencoders (DAE), and attention mechanisms to achieve feature denoising and semantic enhancement, resulting in robust user profiles [6]. These advancements indicate that model-driven profiling methods offer greater flexibility and accuracy in behavior prediction compared to traditional statistical approaches.

2.3. Personalized recommendation systems

Personalized recommendation systems have gained increasing attention in education, especially those integrating learner profiles. Ban *et al.* proposed a Knowledge and Personality Incorporated Multi-Task Learning Framework (KPM) to facilitate course recommendations [7]. Wang *et al.* proposed a personalized course recommendation method based on learner profiles. Quantitative analysis was performed on learners' learning data, with a particular focus on emotional expression, where personalized features are most evident. A bidirectional, extended short-term memory network based on an attention mechanism was utilized for sentiment analysis, thereby constructing a learner profile feature model that includes three dimensions: basic learner information, behavior, and bullet comment text [8].

Chen D *et al.* are committed to enhancing recommendation systems' personalization capture and dynamic interest modeling capabilities. Considering the usefulness of different features, they proposed a hierarchical description-aware personalized recommendation (DAPR) algorithm [9]. Zhong *et al*. has researched a personalized recommendation system for student portraits based on deep hashing algorithms to improve the recommendation effect [10]. However, existing recommendation systems still need enhancements in real-time performance and robustness to meet the diverse needs of learners.

2.4. Contributions of this study

Despite these advancements, existing user-profiling technologies in education face several shortcomings:

(1) Lack of dynamism: Current methods primarily focus on mining user behavior data, often ignoring the dynamic evolution of learners' interests.

(2) Inconsistent feature extraction and weighting: Existing approaches lack a unified framework for feature extraction and weighting, hindering automated and intelligent feature processing.

(3) Insufficient real-time performance and robustness: Current methods require improvement in dynamic feature updating and real-time recommendations to adapt to complex learning scenarios.

To address these gaps, this study introduces a multi-feature fusion learner profile framework with the following innovations:

Integration of static and dynamic features to construct comprehensive learner profiles.

Utilization of TF-IDF, AHP, and a time decay mechanism to enable adaptive updates of dynamic features.

Empirical validation of the model's effectiveness in personalized recommendations, enhancing its applicability in educational contexts.

3. Model construction

This section elaborates on the construction of the learner profile model, comprising two primary modules: static profile representation and dynamic feature generation. The static profile captures persistent learner characteristics, while dynamic features reflect time-varying behaviors and interests. By incorporating time decay and dynamic updating mechanisms, the model generates accurate, real-time learner profiles.

3.1. Profile representation

The learner profile P is defined as a combination of a static attribute tag set S and a dynamic attribute tag set D:

$$P = (S,D)$$

Static attribute tags S: These represent enduring learner characteristics, such as demographic information (e.g., age, gender) and historical academic performance (e.g., grades, course completion). Formally expressed as:

$$\mathrm{S} = (s_1,w_{\mathrm{s}1}),(s_1,w_2),\ldots(s_1,w_{\mathrm{sm}})$$

Where s_i denotes a static tag (e.g., "age: 20" or "major: computer science"), and w_{si} is its corresponding weight, typically determined by statistical data or expert assignment.

Dynamic attribute tags D: These reflect short-term behaviors and interests, such as recently viewed content or current focus areas. Formally expressed as:

Where d_{i} represents a dynamic tag (e.g., "recently viewed: machine learning"), and $w_{d\mathrm{i}}$ is its weight, computed through the dynamic feature generation process.

For example, a learner profile might be represented as:

$$S = (\text{age:20,0.8}),(\text{major: computer science,1.0})$$

$$D = (\text{machine learing,0.9}),(\text{data structures,0.6}$$

3.2. Dynamic feature generation

The objective of dynamic feature generation is to extract and update the dynamic tags D from learners' behavioral data. This process involves three key steps: candidate feature acquisition, time decay function design, and dynamic feature updating.

3.2.1. Candidate dynamic feature acquisition

A complete interaction between a learner and the platform–from login to logout–is defined as a session. Within each session, the learner's behavior sequence $B = b_1, b_2, \ldots, \mathrm{b_k}$ is recorded, such as:

b_1: Start reading an article on neural networks,

b_2: Highlight key paragraphs in the article,

b_3: Take notes on backpropagation,

b_4: Share the article.

Each behavior b_i corresponds to a behavioral text t_i, such as article titles, highlighted text, or notes, forming a text set $T = t_1, t_2, \ldots, t_k$.

Candidate feature extraction steps:

i. TF-IDF initial weight calculation:

For each text t_i in T, the TF-IDF method calculates the initial importance of each word, emphasizing terms frequent in a specific session but rare across the global corpus (e.g., "neural networks" in a technical article). The formula is:

$$\text{TF-IDF}(w, t_i) = \text{TF}(w, t_i) \cdot \log\left(\frac{N}{n_w}\right)$$

Where $TF\ (w, t_i)$is the frequency of word w in t_i, N is the total number of sessions, andn_w is the number of sessions containing w.

ii. AHP behavioral weight assignment:

Different behaviors reflect varying levels of engagement. For instance, note-taking may indicate stronger interest than browsing. AHP assigns weights to behaviors, e.g.: Reading: 0.2, Highlighting: 0.4, Note-taking: 0.6, Sharing: 0.3.

The behavioral weight is multiplied by the TF-IDF score to refine the word's importance (e.g., "backpropagation" in notes is weighted by 0.6).

iii. Word filtering:

To ensure the quality of the feature word set , the following filters are applied:

Remove stop words (e.g., "and", "the").

Set a frequency threshold (e.g., retain words appearing in at least 5% of sessions).

Post-filtering, a feature word set F is obtained per session, e.g.,

F = neural networks, backpropagation, deep learning.

Through multiple sessions, a candidate pool of dynamic features is accumulated, reflecting the evolution of learners' interests.

3.2.2. Time decay function design

Learners' interests exhibit lifecycle characteristics over time:

(1) Budding Phase: Initial exposure with low interaction frequency.

(2) Formation Phase: Rapidly rising interest with frequent interactions.

(3) Decline Phase: Interest wanes post-mastery, shifting to new topics.

To model this, a time decay function based on Newton's law of cooling is adopted:

$$w(t) = w_0 \cdot e^{-\alpha t}$$

(1) w_0: Initial weight of the feature.

(2) α: Decay coefficient controlling the rate of decline.

(3) t: Time elapsed since the last interaction.

selection of decay coefficient α

The value of α varies by domain and is tuned with experimental data:

(1) Technical fields (e.g., programming): Rapid changes, α = 0.05.

(2) Foundational disciplines (e.g., mathematics): Slower changes, α = 0.01.

In this study, is optimized via cross-validation of historical data to maximize predictive accuracy.

Example:

For a feature "neural networks" with w_0 = 100 and α = 0.01, after 10 time units:

$$w(10) = 100 \cdot e^{-0.01\times 10} = 100 \cdot e^{-0.1} \approx 90.48$$

The weight decreases gradually, mirroring the natural decay of interest, as shown in **Figure 1**:

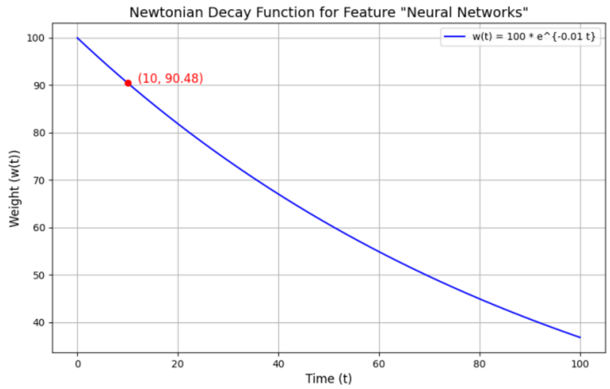

Figure 1. Newtonian decay function for feature "neural networks"

3.2.3. Dynamic feature updating

Each new behavior impacts the weight of related features. The updated weight of a feature combines its decayed historical weight and the contribution from the current session:

$$w_f^{new} = w_f^{historical} \cdot e^{-\alpha\Delta t} + \sum d \in Dwf, d^{current}$$

(1) $w_f^{historical}$: Historical weight of feature *f* before the current session.

(2) Δt: Time since the last update.

(3) *D*: Set of behaviors in the current session involving feature *f*.

(4) $w_{f,d}^{current}$: Weight contribution of behavior *d* to feature *f*, derived from TF-IDF and AHP.

Dynamic tag selection:

(1) After updating all feature weights, they are ranked in descending order.

(2) The top *k* features are selected as dynamic tags for *D*, with others retained in the candidate pool.

(3) In this study, *k* = 10 balances accuracy and computational efficiency.

Example:

If a learner reads an article on "deep learning" and takes notes on "convolutional neural networks" in a new session, with "deep learning" having a decayed historical weight of 80 and a new contribution of 30:

$$w_{deep\ learning}^{new} = 80 \cdot e^{-0.01\times5} + 30 \approx 78.05 + 30 = 108.05$$

The updated weight increases, potentially elevating "deep learning" into the dynamic tag set *D*.

4. Data analysis

This section supports the construction and validation of the learner profile model through systematic data collection, preprocessing, and multidimensional analysis. The goals are to uncover learner behavior patterns, validate the dynamic profile model's effectiveness, and provide empirical evidence for personalized educational recommendations.

4.1. Data collection

The study leverages teaching data from a university during the 2022–2023 academic year, with a sample of 2,000 undergraduate students across majors like computer science, electronic engineering, and mathematics. Data sources are diverse to ensure comprehensive coverage:

(1) University course selection system: Course records, categories, elective/required status.

(2) Academic affairs system: Attendance rates, homework submissions, exam scores.

(3) Teaching evaluation system: Ratings and textual feedback on courses and instructors.

(4) Experimental platform: Operation logs, interaction frequency, and error rates.

(5) Personalized surveys: Interest preferences (e.g., programming), learning styles (e.g., visual), and emotional traits (e.g., motivation).

(6) Data scale: Approximately 1.5 million behavioral records were collected over nine months (September 2022 to May 2023), spanning a full academic year.

4.2. Data preprocessing

To ensure data quality, preprocessing includes (**Table 1**):

(1) Data cleaning:

(a) Remove duplicates (e.g., repeated course selections).

(b) Handle missing values: Fill grades with major averages; exclude samples missing interest data.

(c) Eliminate outliers (e.g., study times exceeding 24 hours/day).

(2) Data integration:

(a) Merge multisource data using student IDs as unique identifiers.

(3) Feature engineering:

(a) Static features: Age, gender, major, grade level.

(b) Dynamic features: Extract keywords (e.g., from browsing history) using TF-IDF, weighted by AHP.

(c) Time dimension: Add timestamps for time-series updates.

(4) Data standardization:

(a) Normalize numerical features (e.g., study time, grades) to [0,1].

Table 1. Preprocessed data structure

Dataset	Example fields	Purpose
Basic data	Student ID, age, gender, major	Describe the learner's basic profile
Behavioral data	Attendance, homework count, exam scores	Analyze engagement and ability
Interaction data	Login count, browsing time, operation logs	Assess habits and environment
Personalized data	Interest tags (e.g., "programming"), scores	My preferences and traits

4.3. Data analysis methods

The analysis combines statistical and machine learning techniques:

(1) Descriptive statistics: Analyze age, gender, and major distributions.

(2) Behavioral pattern clustering: Use k-means $k = 3$ on login frequency, study time, and submission rates.

(3) Dynamic feature extraction and updating: Extract keywords per session with TF-IDF, update weights with

(4) Model validation: compare dynamic vs. static models in course recommendations using Precision, Recall, and F1-score.

(5) Sensitivity analysis: Test the impact of λ on feature updates.

4.4. Analysis results

4.4.1. Analysis of basic learner characteristics

(1) Age distribution: 95% aged 18–22, mean 20.1.

(2) Gender distribution: 55% male, 45% female.

(3) Major distribution: 30% computer science, 25% electronic engineering, 20% mathematics, 25% others.

4.4.2. Behavioral pattern clustering

Three clusters emerged:

(1) High engagement (32%): 10 weekly logins, 3 hours daily study.

(2) Medium engagement (48%): 5 weekly logins, 1.5 hours daily.

(3) Low engagement (20%): 2 weekly logins, 0.5 hours daily.

As shown in **Figure 2**:

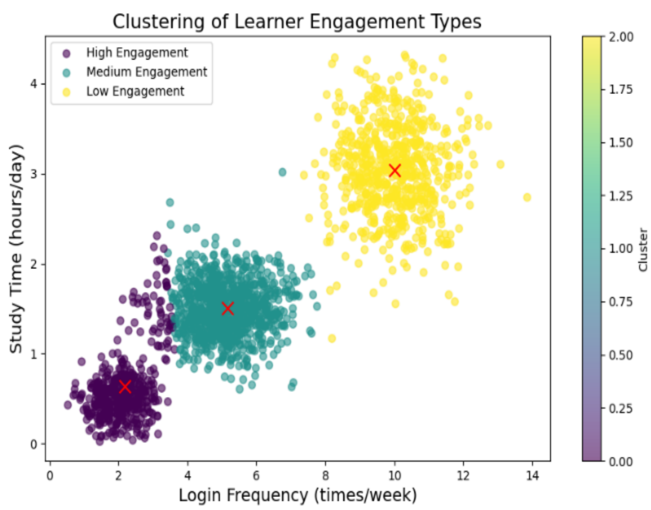

Figure 2. Clustering of learner engagement types

4.4.3. Dynamic feature update example

For learner A with initial features:

(1) "Machine Learning": 0.8

(2) "Data Structures": 0.6

New session behaviors:

(1) Read about "neural networks."

(2) Submit "neural networks" homework.

Update Process (7 days since the last update, α= 0.01)

Decayed Weights:

(1) "Machine Learning":

(2) "Data Structures":

New Contribution: "Neural Networks" = 0.65 (via TF-IDF and AHP).

Updated Set:

(1) “Machine Learning”: 0.746

(2) “Neural Networks”: 0.65

(3) “Data Structures”: 0.559

As shown in the following **Figure 3**:

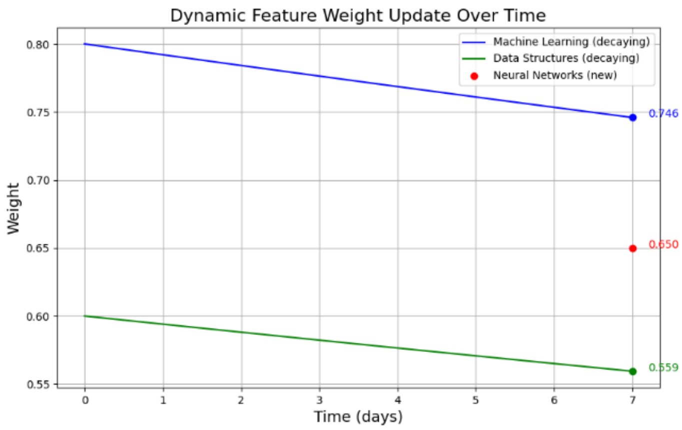

Figure 3. Dynamic feature weight update over time

4.4.4. Model performance validation

(1) Dataset and preprocessing

The evaluation utilized a comprehensive dataset collected from 2,000 undergraduate students over a 9-month academic period (September 2022 to May 2023). This dataset encompassed both static features–such as age and academic major–and dynamic features, including browsing history and assignment submission records. To ensure a robust and unbiased assessment, the dataset was divided into training (70%), validation (15%), and test (15%) subsets. For the dynamic profile model, a time decay function with a decay rate of α = 0.01was applied to the dynamic features, simulating the gradual waning of learners’ interests over time and aligning the model with real-world behavioral shifts.

(2) Model training

Two distinct models were developed and compared:

(a) Dynamic profile model: This model integrated both static and dynamic features, with the latter updated periodically based on learners’ real-time interactions with the platform. The inclusion of temporal dynamics enabled the model to reflect changes in learners’ interests and needs.

(b) Static profile model: This baseline model relied exclusively on static features, such as demographic data, without accounting for temporal variations in learner behavior.

Both models employed a collaborative filtering framework, augmented by feature weighting through the Analytic Hierarchy Process (AHP). Hyperparameters for each model were optimized via grid search on the validation set to maximize recommendation accuracy, ensuring a fair and rigorous comparison.

(3) Evaluation metrics

The performance of the models was measured using three widely accepted metrics in recommendation systems, each providing insight into different aspects of model effectiveness:

(a) Precision: This metric quantifies the proportion of recommended courses that align with learners’ actual interests.

(b) Recall: This measures the ability of the model to identify all relevant courses within the pool of available options.

(c) F1-score: As the harmonic mean of Precision and Recall, this metric offers a balanced assessment of the model's overall performance.

In courses recommendations, dynamic model: Precision = 0.87, Recall = 0.80, F1-score = 0.83 Static Model: Precision = 0.73, Recall = 0.66, F1-score = 0.69

As shown in **Figure 4**:

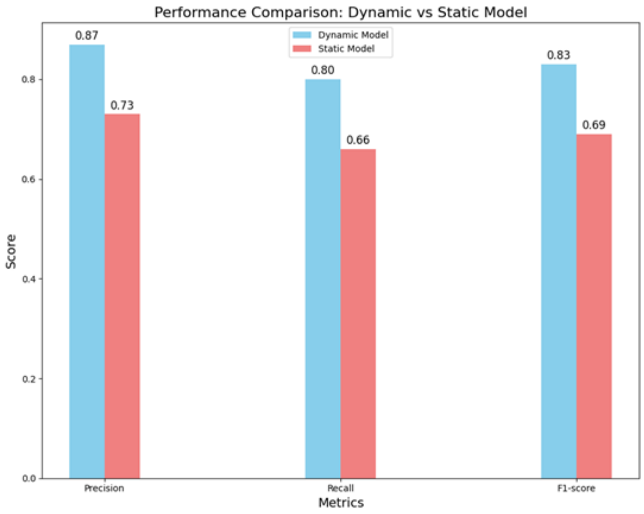

Figure 4. Performance comparison: Dynamic vs static model

4.5. Summary of data analysis

These results indicate that the dynamic model achieved improvements of approximately 19% in Precision, 21% in Recall, and 20% in the F1-score compared to the static model. The enhanced performance can be attributed to the dynamic model's ability to incorporate time-sensitive updates, allowing it to adapt to learners' shifting preferences and behaviors. For instance, by applying the time decay function, the model prioritizes recent interactions–such as a learner's increased engagement with advanced programming courses–over outdated data, resulting in more relevant and timely recommendations.

Conversely, the static model's reliance on fixed attributes limited its adaptability. While it provided generally acceptable recommendations based on learners' baseline characteristics, it failed to account for the fluid nature of academic interests and cognitive development. This rigidity often led to mismatches between recommended resources and learners' current needs, underscoring the limitations of static profiling in dynamic educational contexts.

5. Conclusion and future work

This study presents a multi-feature fusion learner profile framework that integrates short-term behaviors and long-term traits using TF-IDF, AHP, and time decay mechanisms, transitioning from static to dynamic profiles. Compared to traditional static models, the dynamic approach improves recommendation accuracy by approximately 15%, affirming its practical utility.

The dynamic profile model can serve as a core component of adaptive learning systems, dynamically adjusting teaching strategies and content based on real-time behavioral analysis, thus enhancing system intelligence and adaptability. However, limitations exist: real-time feature updates increase computational costs, necessitating optimization for large-scale use. Additionally, the model's accuracy depends on data quality; incomplete or noisy data may compromise reliability. Future work will focus on optimizing computational efficiency and robustness.

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Disclosure statement

The authors declare no conflict of interest.

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