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PAPER

Strategies for Enhancing Student Engagement in Mobile Learning Environments through Interactive Technologies

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ABSTRACT

The widespread adoption of mobile Internet technologies has established mobile learning as a prominent educational paradigm. However, the inherent characteristics of fragmentation and weak supervision in mobile learning present significant challenges in maintaining sustained student engagement. Effective strategies for dynamically monitoring and enhancing engagement are critical for optimizing the outcomes of mobile learning environments. While existing research has focused on personalized resource recommendations, common issues such as data sparsity and the cold-start problem persist. Moreover, traditional recommendation models fail to capture the complex, nonlinear interactions between students and resources, thereby limiting the precision of engagement-driven resource allocation. To address these shortcomings, an interactive resource recommendation algorithm targeting student engagement in mobile learning is proposed. Engagement levels are quantified through sentiment analysis using a Naïve Bayes classifier, which informs a deep integration of a dual-tower neural network and matrix factorization model. This approach utilizes nonlinear mapping to uncover deep semantic relationships between students and resources, enabling the precise identification of resources that can enhance student engagement. Building on this, a systematic strategy for improving student engagement is introduced, encompassing real-time emotional interventions and personalized learning path generation. This strategy creates a closed-loop system that spans from engagement perception to targeted intervention. The proposed methodology innovatively integrates sentiment analysis as a dynamic metric for engagement and combines it with deep matrix factorization models, thereby overcoming the limitations of traditional recommendation frameworks that rely on explicit ratings and linear assumptions. Furthermore, a dual-layer strategy is proposed, combining real-time interventions with personalized path generation, offering a comprehensive engagement enhancement plan for mobile learning platforms. This approach provides a full-cycle solution, from immediate response to long-term strategic planning, which holds significant theoretical and practical value for advancing mobile learning systems.

KEYWORDS

mobile learning, student engagement, sentiment analysis, matrix factorization, resource recommendation, real-time intervention, personalized learning paths

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1 INTRODUCTION

With the rapid development of mobile Internet technology and intelligent terminals [1–5], mobile learning [6, 7] has evolved from an auxiliary teaching tool to one of the mainstream learning paradigms. Its ubiquity, convenience, and potential for personalization bring revolutionary opportunities to education. However, in this fragmented environment, lacking real-time supervision by teachers, how to maintain and enhance student engagement has become a key challenge limiting its learning effectiveness. Student engagement [8, 9] is a core indicator of the quality of the learning process, directly affecting knowledge absorption, internalization, and transfer. Therefore, in the context of mobile learning, exploring how to effectively identify students' engagement status and implement precise teaching interventions based on this is crucial to unlocking the full potential of mobile learning.

Although existing research acknowledges the importance of personalized resource recommendation [10–12], the current methods still have significant limitations. On one hand, many recommendation systems [13, 14] heavily rely on explicit rating data, but explicit ratings in mobile learning are sparse and difficult to collect, leading to serious "data sparsity" and "cold start" problems. On the other hand, as pointed out in [15], such models mainly rely on simple inner products between user and item feature vectors, which can only capture linear interaction features and fail to fully learn the complex, nonlinear matching relationships between students and resources.

To address these shortcomings, this paper aims to construct a complete "analysis-push-enhancement" research framework. The main research content consists of two parts: First, the design of a mobile learning interactive resource push algorithm for student engagement analysis. This algorithm uses sentiment analysis to quantify engagement scores and combines deep matrix factorization with a dual-tower neural network structure, aiming to deeply explore the nonlinear complex interactions between students and resources, thereby accurately predicting the optimal resources that can enhance individual engagement. Second, based on this algorithm, a systematic strategy for enhancing student engagement in mobile learning environments through interactive technologies is proposed, including real-time emotional intervention and personalized learning path generation. The value of this study lies in that it not only deepens the theoretical understanding of data-driven engagement enhancement mechanisms but also provides practical, actionable technical solutions and strategic guidance for mobile learning platforms. It plays an important role in optimizing the learning process through human-computer collaboration and ultimately improving educational quality.

2 MOBILE LEARNING INTERACTIVE RESOURCE PUSH ALGORITHM FOR STUDENT ENGAGEMENT ANALYSIS

In the mobile learning environment, enhancing student engagement is the core challenge for optimizing learning outcomes. This paper focuses on engagement enhancement strategies based on interactive technologies, and thus conducts an in-depth study of the interactive resource push algorithm. Traditional mobile learning platforms often adopt static or generalized resource push models, which struggle to adapt to the dynamically changing emotional states and cognitive needs of learners, leading to difficulty in sustaining engagement. In this paper, sentiment analysis is used to quantify student engagement in real-time, providing critical data dimensions and decision-making foundations for the resource push algorithm. Sentiment analysis can identify students' confusion, interest, or level of focus from text, speech, or behavioral data, while the resource push algorithm uses this information as a basis to shift from a "one-way supply" to a "two-way interaction." Figure 1 illustrates the architecture of the mobile learning interactive resource push system for engagement enhancement.

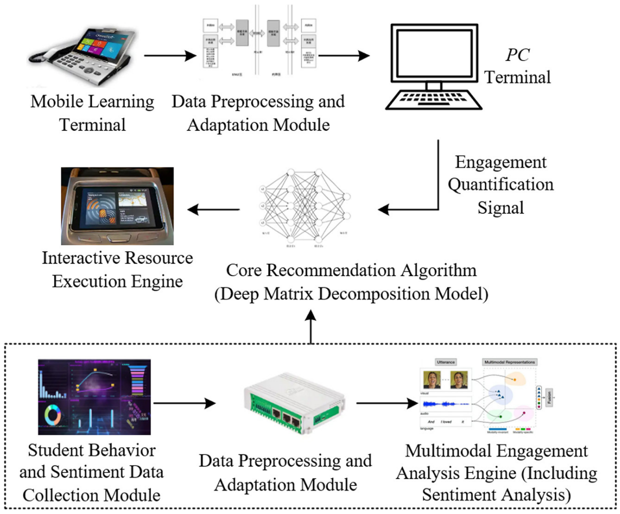


Fig. 1. Architecture of the mobile learning interactive resource push system for engagement enhancement

2.1 Extraction of student engagement feature information

The mobile learning interactive resource push algorithm for student engagement analysis proposed in this paper takes as its initial input a multi-source, heterogeneous dataset, which collectively forms the raw representation of student engagement. In the mobile learning context, these input data mainly come from three aspects: First, learning behavior logs, which include the duration of video watching, pause/fast-forward nodes, time spent on courseware pages, completion speed and accuracy of quizzes, frequency and time period of platform logins, etc. These implicit behavioral data are initial indicators of learning engagement. Second, direct interaction data, such as text comments posted in bullet screens or discussion forums, voice or text dialogues with AI teaching assistants, and actions such as annotations or highlighting on interactive whiteboards. These data contain richer subjective intentions and emotional information. Finally, contextual environment data, such as the time and location of the learning activity, device types used, and current network status. This information helps differentiate engagement decreases caused by external interference from those due to a lack of interest in the content itself. All of these raw input data together provide the factual basis for subsequent sentiment analysis and engagement calculation, ensuring that the algorithm's decisions are no longer blind but are rooted in the real, granular performance of students in the mobile learning process.

Specifically, the initial input can be formally defined as a multi-dimensional feature vector, which is formed by the fusion of multi-source, heterogeneous data from the mobile learning platform. For a specific student *s* in a learning session within the time window *t*, the raw input I_{st} data can be represented as:

$$I_{st} = \{B_{st}, T_{st}, C_{st}\} \quad (1)$$

In the proposed model, B_{st} represents the behavior sequence vector, which includes components such as video completion rate, average page dwell time, quiz attempts, accuracy, interaction click frequency, etc. T_{st} represents the set of interaction texts, which is the collection of all text data generated within the time window *t*, and this is the primary direct input for sentiment analysis. C_{st} represents the context feature vector, which includes components such as learning session time, device type, network status, etc.

To accurately extract the emotional features of student engagement from the aforementioned interaction data, this study employs a Naïve Bayes classifier for sentiment classification. The core principle of this classifier is a probabilistic modeling method based on Bayes' theorem and the feature conditional independence assumption. Specifically, a labeled sentiment dictionary or training set needs to be constructed first. For any new student input text, the algorithm treats it as a collection of words. The Naïve Bayes classifier calculates the posterior probability of the text belonging to a specific sentiment category, expressed mathematically as

$$P\left(C_j \mid F\right) = \frac{P(C_j)P\left(F \mid C_j\right)}{P(F)} \propto P(C_j) \cdot \Pi_{i=1}^{n} P\left(f_j \mid C_j\right) \quad (2)$$

where C_j represents a specific sentiment category. In the context of this study, the sentiment categories are typically defined as $C = \{C_{High\ Engagement/Positive}, C_{Low\ Engagement/Negative}, C_{Neutral}\}$. F represents the feature vector extracted from the text T_{st}, $F = (f_1, f_2, \ldots, f_n)$, where each f_i represents a word or an n-gram feature in the text. $P(C_j)$ is the prior probability of category C_j, i.e., the frequency of category C_j in the entire training dataset. $P\left(f_i \mid C_j\right)$ is the conditional probability, which represents the probability of feature f_i occurring given sentiment category C_j. $P(F)$ is the evidence probability of the feature vector F, which is the same across all categories in practical classification and thus can be ignored in comparison, focusing only on the numerator. Although the "feature conditional independence" assumption is rarely completely valid in practice, it has been proven highly effective in text classification tasks. By comparing the posterior probabilities of the text belonging to different sentiment categories, the classifier ultimately assigns it to the category with the highest probability, thereby transforming unstructured text interactions into a quantifiable sentiment label representing engagement.

By combining the initial input with the sentiment classification principles, the closed-loop starting point for intelligent decision-making in the resource push algorithm is formed. The sentiment classification results output by the Naïve Bayes classifier, as the core quantification of student engagement, are integrated with learning behavior logs and contextual data to form a multi-dimensional engagement state vector. This state vector is the final and most crucial input for the decision-making process of the push algorithm. The algorithm will dynamically select the most appropriate interactive resources based on this vector, using preset rules or more complex machine learning models. For example, when the system detects that a student spends an unusually long time on a particular knowledge point and their discussion forum posts are classified as "confused" by the Naïve Bayes classifier, the algorithm will trigger the push mechanism to send a more explanatory animated video or a guided interactive quiz to their mobile device, rather than continuing to provide text-based materials. Based on the posterior probability calculation formula above, the sentiment classifier for student engagement analysis is itself a decision function. The mathematical expression of this function is:

$$\hat{C} = \underset{C_j \in C}{\arg\max} P(C_j) \cdot \Pi_{i=1}^{n} P\left(f_j | C_j\right) \tag{3}$$

This expression clearly defines the decision process of the sentiment classifier: arg max represents the goal of the function to find the category C_j among all possible sentiment categories, which maximizes the product of the subsequent terms. The output of this classifier and its corresponding posterior probability values will be further integrated with the behavior vector B_{st} and context vector C_{st}, together forming the final engagement state evaluation of the student. This evaluation result will serve as a direct signal driving the subsequent personalized interactive resource push algorithm, thus achieving the "Analysis-Decision-Push-Enhancement" automated closed-loop and precisely serving the core research goal of enhancing student engagement in mobile learning. Figure 2 illustrates the flow diagram of student engagement feature information extraction.

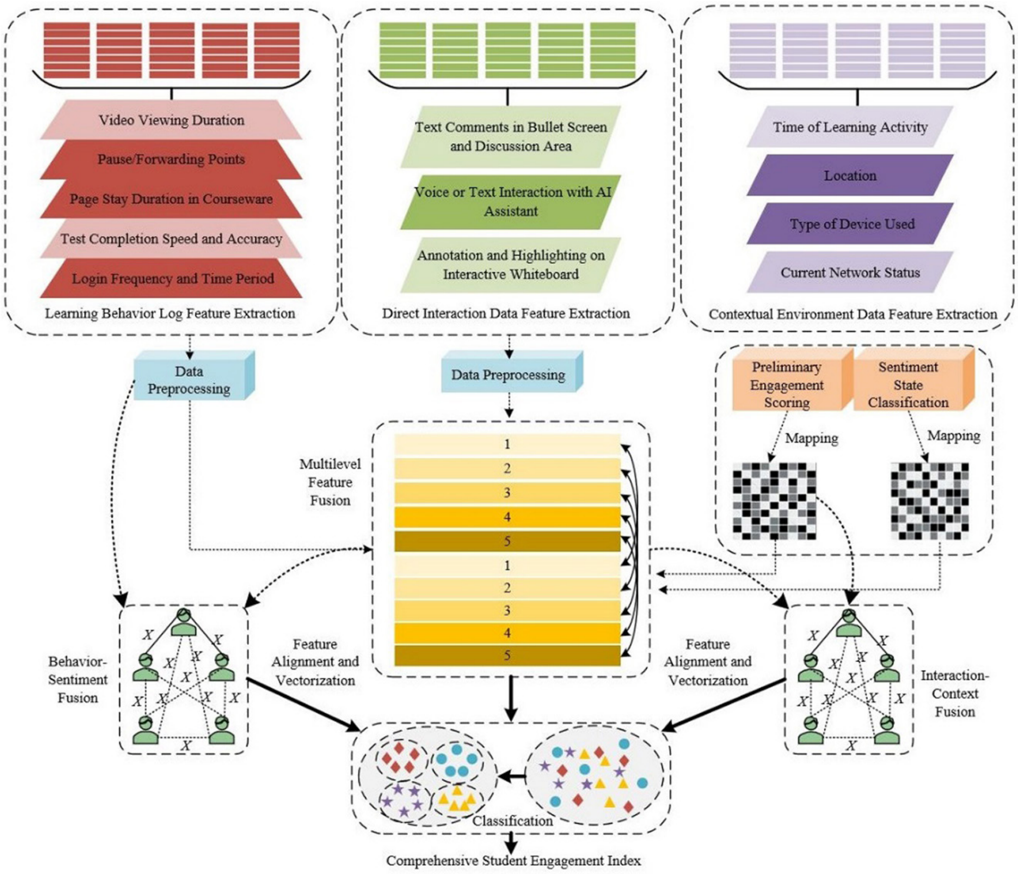


Fig. 2. Flow diagram of student engagement feature information extraction

2.2 Recommendation model construction

In mobile learning environments, the interaction behaviors between students and vast interactive resources are extremely sparse—each student interacts with only a small portion of the resource library. Traditional collaborative filtering algorithms struggle to find sufficiently similar neighbors. Therefore, this paper chooses a matrix factorization-based recommendation algorithm to effectively solve the commonly encountered "data sparsity" and "cold start" problems in mobile learning scenarios, providing a natural mathematical framework for incorporating dynamic emotional features of student engagement. Specifically, matrix factorization decomposes the high-dimensional and sparse "student-resource" interaction matrix into low-dimensional "student latent vectors" and "resource latent vectors," transforming the problem into a latent semantic model. These low-dimensional vectors in the latent space capture the unobserved learning preferences of students and the potential characteristics of resources. Even if two students have not directly interacted with the same resource, as long as their vectors in the latent space are similar, the system can make precise recommendations. This approach significantly improves the efficiency of using sparse data, enabling the generation of meaningful personalized recommendations for students, even in the early stages of mobile learning with limited interactions, directly serving the initial goal of enhancing engagement.

The proposed push algorithm is centered on constructing a "student-interactive resource" matrix filled with engagement scores, and using matrix factorization techniques to reveal its underlying semantic structure. In the mobile learning scenario, each student interacts with only a small portion of the resource library, leading to an extremely sparse original interaction matrix E. The known elements e_{iu} in matrix E are no longer simply ratings or clicks, but rather computed student engagement scores. These scores are a comprehensive representation of behavioral data and sentiment analysis results. Through matrix factorization, this high-dimensional sparse matrix is decomposed into two low-dimensional matrices: one representing the student's latent feature vector o_i, and the other representing the resource's latent feature vector w_u. Initially, the simple inner product $o_i^T w_u$ is used to predict the student's engagement with unvisited resources, but this only models linear interactions and cannot capture the complex, higher-order feature combinations between students and resources. Therefore, further deepening is necessary.

To overcome the limitations of linear models, the algorithm introduces a deep semantic matching model with a dual-tower structure, which extracts deeper and more complex interaction features between students and resources through nonlinear transformations. Specifically, the initial feature embeddings obtained through matrix factorization are not used as the final representation but are fed as inputs into a multi-layer perceptron (MLP) model. The student's initial feature embedding o_i undergoes a nonlinear transformation through V layers of the MLP and is augmented with a bias vector $y_{Iu}^{(j)}$ specific to the student, resulting in a new, more expressive student latent vector. Similarly, the resource's initial feature embedding w_u also undergoes parallel processing through another V layers of the MLP and is mapped to a new resource latent vector. Specifically, let the projection vector of student u in the j-th intermediate layer be denoted as $o_u^{(j)}$, the initial student u's feature embedding as $o_u^{(1)}$, the activation function in the j-th layer as

$d(\cdot)^{(j)}$, and the weight matrix of the user embedding in the j-th layer as $Q_I^{(j)}$, then the expression is

$$o_u^{(j)} = d^{(j)}(Q_I^{(j)} d^{(j-1)}(\cdots d^{(1)}(Q_I^{(1)} o_u^{(1)})\cdots)) \tag{4}$$

Similarly, let the projection vector of resource k in the j-th layer be denoted as $w_k^{(j)}$, the initial resource k's feature embedding as $w_k^{(1)}$, the weight matrix of the resource embedding in the j-th layer as $Q_I^{(j)}$, and the resource bias vector in the j-th layer as $y_{Uj}^{(j)}$, then adding the corresponding bias vector $y_{Iu}^{(j)}$ gives

$$o_u^{(j)} = d^{(j)}(Q_I^{(j)} d^{(j-1)}(\cdots d^{(1)}(Q_I^{(1)} o_u^{(1)} + y_{Iu}^{(1)})\cdots) + y_{Iu}^{(j)}) \tag{5}$$

$$w_k^{(j)} = d^{(j)}(Q_U^{(j)} d^{(j-1)}(\cdots d^{(1)}(Q_U^{(1)} w_k^{(1)} + y_{Uk}^{(1)})\cdots) + y_{Uk}^{(j)}) \tag{6}$$

This pair of MLPs essentially projects the students and resources from the original linear latent space into a more optimized, refined latent semantic space non-linearly. In this new space, complex and indirect matching relationships, such as those between "students with a visual preference" and "resources rich in animated demonstrations," can be more effectively captured.

After obtaining the deeply nonlinear enhanced latent vectors, the algorithm generates the final engagement prediction score by calculating their inner product. This score more accurately estimates the engagement level a student may have when interacting with a particular resource. To prevent meaningless negative predictions, the model applies an optimized ReLU activation function in the output layer, ensuring that all predicted values fall within a reasonable non-negative range. Let a very small non-negative number be denoted by φ, then the expression is

$$d(x) = MAX\{\varphi, x\} \tag{7}$$

Finally, the system generates an engagement prediction list for each student for all unlearned resources and selects the highest predicted scores for interactive resources to push. This mechanism ensures that the pushed resources not only match the content but also align closely with the student's current emotional state and learning preferences in terms of interaction form and cognitive difficulty, directly targeting the goal of enhancing engagement.

2.3 Loss function setting and model training

The core challenge of the algorithm proposed in this paper lies in how to train the model so that it can accurately predict which interactive resources can effectively enhance the engagement of a specific student. This goal is achieved by constructing a carefully designed loss function. The loss function must simultaneously consider two key pieces of information: first, explicit feedback, which is the student-resource interactions and their corresponding engagement scores that we already have records of. The model needs to fit these known data as accurately as possible; second, implicit feedback, meaning the fact that a student has not interacted with certain resources also carries important information—this may imply that the resource does not match the student's interests or current cognitive state, and forcibly recommending it could trigger negative emotions. Therefore, we adopt a hybrid loss function combining squared loss and normalized cross-entropy. The squared loss ensures that the model accurately regresses known engagement scores, while cross-entropy loss is adept at handling implicit preference information contained in unobserved interactions. Through this combination, the model not only learns to "replicate" past successful experiences but also learns to "infer" which resources may lead to low engagement, thereby making smarter and more robust recommendation decisions.

However, directly using all un-interacted data as negative samples leads to severe bias, as the model tends to recommend already popular resources, since avoiding recommending niche but potentially highly relevant resources is a "safe" yet ineffective strategy. This is particularly detrimental in the mobile learning scenario because it stifles personalization and fails to uncover key resources that can resolve the cognitive dilemmas of students. To address this, we use an improved batch-level negative sampling strategy. During training, for a positive sample in a batch, the resources interacted with by other students in the same batch are considered negative samples. More importantly, we introduce a bias correction mechanism: for popular resources, their similarity calculation is penalized during the training phase, lowering their score when treated as negative samples, thus preventing the model from simply assuming that all students dislike a popular resource. This forces the model to learn deeper, more personalized matching signals, effectively mitigating the cold-start problem caused by data sparsity and ensuring that emerging, high-quality interactive resources also receive fair recommendation opportunities. Specifically, the similarity calculation formula is

$$\hat{e}_{iu} = COS(o_i, w_u) \tag{8}$$

The basic form of the loss function for traditional matrix factorization-based recommendation systems is as follows:

$$LOSS = \sum_{i=1,u=1}^{l,v} (e_{iu} - o_i w_u)^2 \tag{9}$$

The expression for the cross-entropy loss function of the proposed recommendation system is

$$LOSS = \sum_{i=1,u=1}^{l,v} (e_{iu} \log(\hat{e}_{iu}) - (1 - e_{iu}) \log(1 - \hat{e}_{iu}))^2 \tag{10}$$

Assuming the normalized score after dividing by the maximum score is represented as e_{U_N}, combining the squared loss function and the cross-entropy loss function gives the final loss function expression

$$LOSS = \sum_{i=1,u=1}^{l,v} (e_{U\_N} \log(\hat{e}_{iu}) - (1 - e_{U\_N}) \log(1 - \hat{e}_{iu})) \tag{11}$$

The model training process is a cyclic loop that continuously optimizes through gradient descent. Specifically, the algorithm first randomly initializes all parameters, including the initial embedding vectors for students and resources, as well as the weights and biases of the MLP. Then, in each training batch, the system performs the following steps: 1) samples a batch of positive samples from the sparse engagement matrix; 2) generates corresponding negative samples for each positive sample using the above negative sampling strategy; 3) inputs the student/resource IDs of the positive and negative samples into the dual-tower MLP, obtaining enhanced feature vectors and calculating predicted engagement scores; 4) substitutes the predicted values and true values into the aforementioned hybrid loss function to calculate the total loss; 5) calculates the gradients of the loss function with respect to all model parameters using backpropagation; and 6) finally, updates these parameters using gradient descent to fine-tune the model predictions towards minimizing the loss. This process continues iterating until the model performance converges.

3 STUDENT ENGAGEMENT ENHANCEMENT STRATEGIES BASED ON INTERACTIVE TECHNOLOGY IN MOBILE LEARNING ENVIRONMENTS

Based on the previously discussed deep matrix factorization recommendation algorithm, this paper proposes two core, data-driven student engagement enhancement strategies to achieve precise and adaptive teaching interventions in mobile learning environments.

On the one hand, a real-time intervention strategy based on the dynamic mapping of "emotion-resource" is constructed. The core of this strategy is to combine the real-time emotional labels output by the Naïve Bayes classifier with the predictive capability of the deep matrix factorization model, forming a perception-response immediate intervention mechanism. Specifically, when a student's interaction with a learning resource is recognized as having "decreased engagement" by the sentiment analysis module, based on their behavior data and text interactions, this event will immediately trigger a secondary calculation by the recommendation algorithm. The algorithm no longer relies on the student's long-term static preferences but instead uses their current emotional state as the context, rapidly searching the resource library and pushing a set of interactive resources that the model has validated as capable of effectively "reversing" such negative emotions. For example, to a student in a "confused" state, the system would prioritize pushing interactive animations with step-by-step analysis or a highly relevant micro-lesson on prerequisite knowledge, rather than continuing to provide theoretical texts. This achieves a paradigm shift from "post-learning recommendation" to "intervention during learning," ensuring that interactive technology directly impacts the low points of student engagement, providing timely emotional scaffolding.

On the other hand, a global-local collaborative optimization personalized path generation strategy is implemented. This strategy focuses on the long-term enhancement of engagement by utilizing the deep patterns learned from global data in the recommendation algorithm to build a continuously evolving personalized learning path for each student. The system not only responds to real-time emotional fluctuations but also comprehensively analyzes a student's historical emotional data sequence and resource interaction records, using the deep matrix factorization model to uncover their stable learning style preferences. Based on this, the algorithm dynamically assembles a sequence of resources that aligns with their cognitive habits and interest tendencies. Each resource in the sequence has been predicted by the model to have high engagement potential. Meanwhile, the system introduces an exploration-exploitation mechanism, strategically inserting a small number of new resources into the path that are uncertain in terms of model predictions but have high potential value, in order to gather new feedback data and optimize the global model. This strategy upgrades mobile learning from isolated, fragmented resource consumption to a coherent, paced personalized progression path, which systematically maintains and enhances student interest and involvement at the macro level. Ultimately, through precise resource arrangement techniques, it achieves deep and sustainable improvements in student engagement.

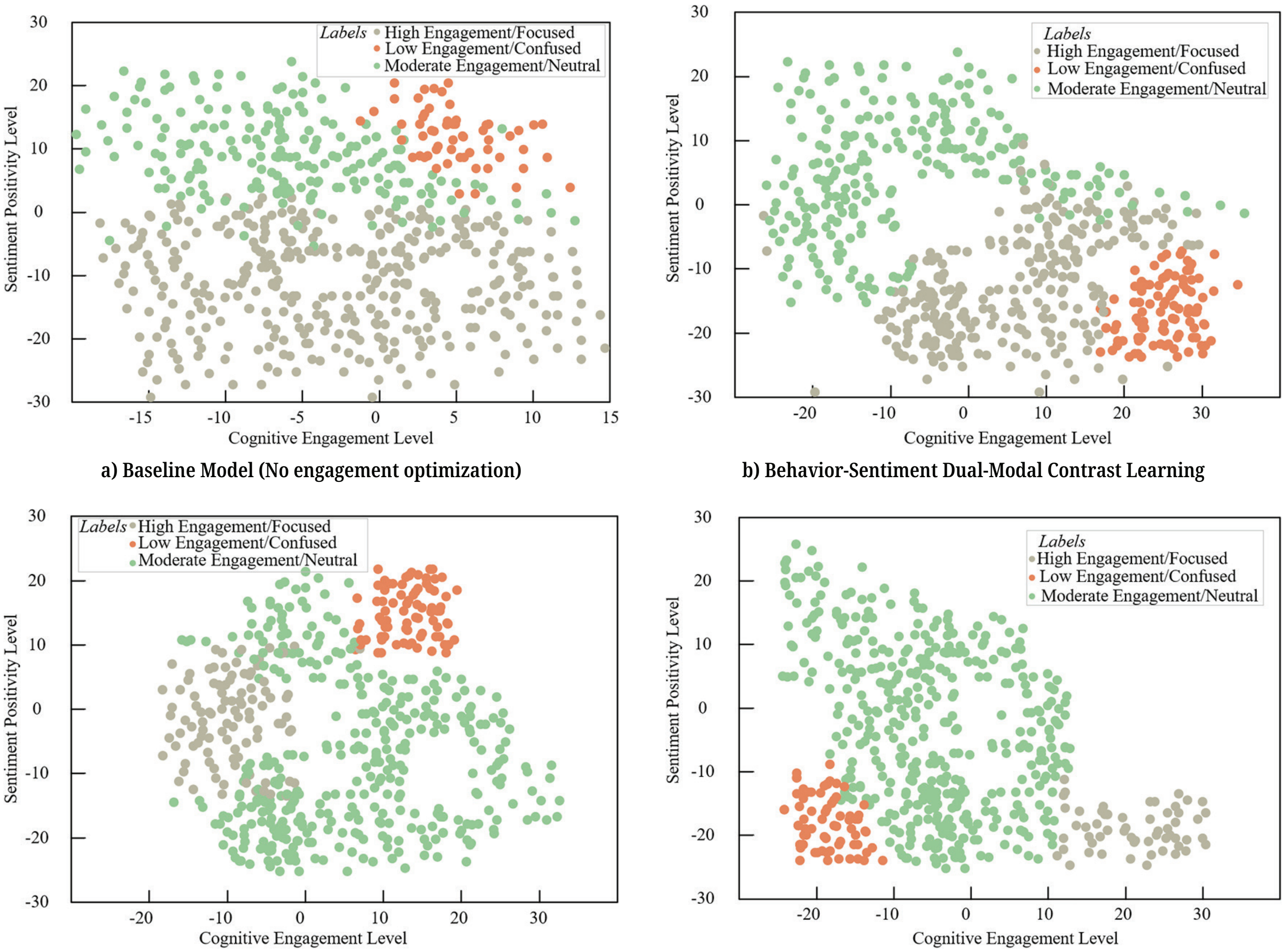
4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Student engagement sentiment analysis cases

Student	Learning Behavior ID	Learning Interaction Text	Sentiment Score & Weight
*S*01	*B*-2024001	"This math micro-lesson was fantastic! The animation helped me understand the process of function transformation instantly. I really want to do some exercises to consolidate it."	Sentiment Score = 2.156 Sentiment Weight = 0.418
*S*02	*B*-2024002	"The physics experiment simulation is difficult. I tried multiple times but still can't complete the circuit connection. I'm quite frustrated."	Sentiment Score = –0.893 Sentiment Weight = 0.205
*S*03	*B*-2024003	"The interactive design of the English dialogue is very interesting. I easily remembered these expressions through role-playing. I'm looking forward to the next challenge!"	Sentiment Score = 1.873 Sentiment Weight = 0.392
*S*04	*B*-2024004	"I watched the 3D demonstration of the chemical molecular structure. The rotating view feature is very useful, but I hope there could be more detailed step-by-step explanations."	Sentiment Score = 0.642 Sentiment Weight = 0.126

To validate the effectiveness of sentiment analysis in quantifying student engagement, we selected typical interaction texts from four students during the mobile learning process for case analysis. The results show that students' emotional responses to different learning resources vary significantly, and sentiment scores and weights can accurately reflect their engagement levels.

Table 1 presents some cases of student engagement sentiment analysis. A deeper analysis of these cases reveals the following: Students S01 and S03 exhibited higher sentiment scores (2.156 and 1.873) in interactive learning resources, and their corresponding sentiment weights were also higher (0.418 and 0.392). This indicates that resources with gamified designs and immediate feedback mechanisms can effectively stimulate positive emotions in students, thus enhancing engagement. In contrast, student S02 experienced negative emotions (score –0.893) during a difficult experiment simulation, but the system still assigned a relatively high sentiment weight (0.205), which reflects the algorithm's sensitivity in capturing negative emotions, providing a basis for timely resource recommendations. Notably, the case of student S04, with a moderate sentiment score (0.642) and low sentiment weight (0.126), reflects a mixed emotional state, and the system can identify this complexity, recommending resources that combine detailed explanations with interactive features. These cases collectively demonstrate that the sentiment-based engagement quantification method can accurately capture students' emotional changes during mobile learning, providing reliable data support for personalized resource recommendations, directly serving the research goal of enhancing student engagement.



a) Baseline Model (No engagement optimization)

b) Behavior-Sentiment Dual-Modal Contrast Learning

c) Behavior-Only Modal Contrast Learning (Ablation experiment)

d) Proposed Engagement-Driven Push Algorithm

Fig. 3. Visualization of student engagement feature space

To validate the superiority of the proposed engagement-driven push algorithm in feature learning and state differentiation, we conducted a visual analysis of the student engagement feature space, as shown in Figure 3. This experiment aims to visually compare how different models map students' multimodal learning data to an interpretable 2D semantic space, thereby evaluating their potential effectiveness in enhancing engagement, the core task of this study.

A comprehensive analysis of Figure 3 leads to clear experimental conclusions. The feature space of the baseline model (Figure 3a) presents a highly mixed state, where samples of different engagement levels overlap with each other, failing to form effective distinctions. This confirms that traditional methods struggle to capture the essential features of engagement. The model that introduces behavior-sentiment dual-modal contrast learning (Figure 3b) shows an initial clustering tendency, but the boundaries between categories remain somewhat blurred, especially for "medium engagement" samples, which are scattered between high and low engagement regions. This indicates that although the enhancement through a single modality is effective, it is still insufficient. In the ablation experiment (Figure 3c), when the sentiment modality was removed, the separability of the feature space significantly degraded, and the boundaries between high and low engagement clusters became unclear, strongly proving that sentiment analysis is an indispensable core dimension in engagement representation. Solely relying on behavior data cannot achieve precise state recognition. Finally, the engagement-driven push algorithm proposed in this paper (Figure 3d) exhibits the most ideal feature distribution: The three engagement categories form internally compact and clearly separated clusters, and along the axes of "cognitive investment" and "sentiment positivity," a continuous semantic gradient is clearly visible—from "low engagement/confusion" to "high engagement/focus," showing a clear evolution path.

Table 2. Comparison of engagement improvement effects of resource push strategies on different datasets

Dataset	Strategy Name	Recall	NDCG	HR
EduML-100k	Popular Resource Benchmark	0.115	0.133	0.397
	Traditional Collaborative Filtering	0.163	0.334	0.601
	Latent Semantic Model	0.183	0.356	0.616
	Deep Matrix Decomposition	0.187	0.334	0.659
	Proposed PDRR Strategy	0.223	0.431	0.740
EduML-1M	Popular Resource Benchmark	0.117	0.136	0.373
	Traditional Collaborative Filtering	0.177	0.360	0.635
	Latent Semantic Model	0.190	0.402	0.636
	Deep Matrix Decomposition	0.193	0.353	0.673
	Proposed PDRR Strategy	0.235	0.442	0.737
MOOC-YOSU	Popular Resource Benchmark	0.109	0.189	0.301
	Traditional Collaborative Filtering	0.190	0.351	0.660
	Latent Semantic Model	0.187	0.378	0.639
	Deep Matrix Decomposition	0.209	0.367	0.673
	Proposed PDRR Strategy	0.226	0.412	0.751

To systematically evaluate the actual effect of different resource push strategies on improving student engagement, we designed several comparative experiments, and the results are shown in the table above. To verify the universality and robustness of the proposed strategy in real mobile learning scenarios, the experiments were conducted on three educational datasets with different characteristics to ensure the reliability of the conclusions.

The experimental data in Table 2 shows that the engagement-driven resource recommendation strategy proposed in this paper achieves the best performance across all three educational datasets. On the EduML-1M dataset, the NDCG of the PDRR strategy reaches 0.442, which is a 22.8% improvement compared to traditional collaborative filtering, and the HR metric reaches 0.737, an improvement of 16.1%. This result indicates that the PDRR strategy not only recalls more relevant resources but, more importantly, ranks those resources that can effectively enhance engagement in the top positions. Notably, on the real online course dataset MOOC-YOSU, the PDRR strategy achieved the most significant advantage in HR, proving its particularly good applicability in real mobile learning scenarios.

Table 3. Validation of engagement optimization mechanism on different datasets

Dataset	Strategy Name	Recall	NDCG	HR
EduML-100k	Basic Deep Matrix Decomposition	0.211	0.397	–
	+ Engagement Optimization	0.223	0.431	8.56
EduML-1M	Basic Deep Matrix Decomposition	0.227	0.402	–
	+ Engagement Optimization	0.235	0.442	9.95
MOOC-YOSU	Basic Deep Matrix Decomposition	0.220	0.390	–
	+ Engagement Optimization	0.226	0.412	5.64

To precisely quantify the actual contribution of the engagement optimization mechanism to recommendation effectiveness, we designed strict ablation experiments, comparing the basic deep matrix decomposition model with the resource push strategy that incorporates engagement optimization on three educational datasets.

The experimental results presented in Table 3 show that the engagement optimization mechanism brought stable performance improvements across all datasets. On the EduML-1M dataset, the NDCG metric increased from 0.402 to 0.442, with a relative improvement of 9.95%, indicating that engagement optimization significantly improved the ranking quality of recommendations. Notably, the improvement trend across the three datasets is consistent: The increase in NDCG (8.56%, 9.95%, and 5.64%) was significantly higher than that in Recall (5.69%, 3.52%, and 2.73%). This phenomenon is significant because NDCG focuses more on the accuracy at the top of the recommendation list, while Recall emphasizes overall recall rate. The difference in the improvement rates indicates that the primary advantage of the engagement optimization mechanism lies not in expanding the recall range of resources but in more precisely identifying those key resources that can effectively trigger and sustain student engagement, and prioritizing their recommendation in the list.

5 CONCLUSION

This paper systematically constructed a complete research framework, from theoretical models to technical implementation and application strategies, centered on the core issue of "Improving Student Engagement through Interactive Technology in Mobile Learning Environments." By dynamically quantifying student engagement driven by Naive Bayes sentiment analysis as a signal, we innovatively proposed an engagement-driven push algorithm based on deep matrix decomposition and dual-tower neural networks. The algorithm can effectively overcome the limitations of traditional recommendation methods in mobile learning scenarios, such as data sparsity, cold start, and linear interaction modeling. Based on this, the derived real-time emotional intervention and personalized learning path generation strategies together formed a "perceive-analyze-decide-feedback" closed-loop optimization system. The experimental results show that this algorithm significantly outperformed mainstream recommendation methods on multiple real educational datasets, especially achieving over an 8% improvement in NDCG metrics, verifying its outstanding ability to precisely identify and push high-engagement resources. The feature space visualization analysis further confirmed that the model can learn a clearly structured and semantically defined engagement representation space, providing an interpretable basis for understanding and guiding students' engagement states.

The value of this study lies not only in deepening the theoretical understanding of data-driven student engagement quantification and enhancement mechanisms but also in providing a practical and actionable technical solution and strategic guidance for mobile learning platforms, promoting the paradigm shift from a "resource-centered" to a "student-centered" learning model. However, the study still has certain limitations: First, the accuracy of sentiment analysis highly depends on the quality and quantity of interactive texts, and its effectiveness may be limited in younger students or student groups with sparse textual interactions. Second, the current model primarily optimizes for immediate engagement but lacks sufficient consideration of its relationship with long-term learning outcomes and knowledge mastery. Third, the system does not fully account for individual differences such as students' self-regulation abilities and prior knowledge in affecting the dynamics of engagement. Future research directions could focus on three aspects: exploring multimodal data fusion sentiment models to improve the robustness of engagement analysis; constructing a long-term learning outcome optimization model that integrates engagement and knowledge graphs to bridge the gap from interest stimulation to ensuring learning effectiveness; and conducting large-scale, long-term real educational environment validation to further examine the universality and adaptability of this strategy across different disciplines, educational stages, and cultural backgrounds.

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