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PAPER

Exploring Blended Learning Models Enhanced by Mobile Interactive Technology in Higher Education

Ye Zhang(✉)

Shijiazhuang University of Applied Technology, Shijiazhuang, China

2018010900@sjzpt.edu.cn

ABSTRACT

With the continuous advancement of information technology, mobile interactive technology has been increasingly applied in higher education, providing robust support for blended learning models. These models integrate the advantages of traditional classroom teaching and online learning, enhancing the flexibility and interactivity of the educational process. In recent years, research on mobile interactive technology and blended learning has expanded. However, most studies have primarily focused on the application of technological tools and platform construction, with limited exploration of specific interaction models and learning experiences. Furthermore, research on student learning objective identification and group stratification have been constrained, failing to effectively meet the needs of personalized learning. In response, this study explores the integration of interaction models and learning experiences within a mobile environment for university students in blended learning settings. Additionally, methods for identifying learning objectives and stratifying student groups based on mobile technology were investigated, aiming to provide theoretical and practical guidance for the implementation of blended learning in higher education.

KEYWORDS

mobile interactive technology, blended learning, interaction models, learning experience, objective identification, student stratification

1 INTRODUCTION

In the context of rapid global advancements in information technology, mobile interactive technology has gradually permeated various sectors, including higher education [1–4]. With the widespread adoption of mobile devices such as smartphones and tablets, learners now have the ability to access knowledge anytime and anywhere. This convenience provides a new support environment for blended learning models [5]. Blended learning integrates the advantages of traditional classroom teaching with online learning, and through the use of mobile interactive technology, the interactivity and flexibility of teaching can be further enhanced.

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This enables students to maintain close communication with both teachers and peers during autonomous learning [6–8]. Consequently, exploring how mobile interactive technology can effectively support blended learning models in higher education has become a prominent area of educational research.

This study holds significant practical implications. Firstly, mobile interactive technology offers modern education new tools, which can optimize the distribution of educational resources and improve both the student learning experience and the quality of teaching [9–12]. Secondly, by fostering interaction between teachers and students via mobile devices, a more diverse and personalized learning environment can be created [13–14]. Furthermore, the use of technological means to identify student learning objectives and behaviors enables educational institutions to design more precise teaching strategies, increasing the efficiency of educational resources and meeting the learning needs of different students.

Although existing research have extensively explored blended learning models, most studies have focused on the application of technological tools or the construction of teaching platforms, with limited systematic analysis of specific interaction model design and the optimization of learning experiences [15–18]. Additionally, the current research on identifying and stratifying student learning objectives has been predominantly limited to single assessment dimensions, which fails to adequately address the diverse needs and characteristics of learning groups. Therefore, further research is required to investigate how mobile interactive technology can enhance the interactive effectiveness of blended learning and to explore effective methods for identifying and stratifying student groups.

This study is divided into two main parts: first, the organic integration of interaction models and blended learning experiences in a mobile environment for university students was examined; second, the identification of student learning objectives through mobile technology and the subsequent stratification of student groups were explored. This study not only provides a theoretical foundation for the support of blended learning models by mobile interactive technology but also offers valuable guidance for practical teaching design, contributing to the innovation and development of higher education.

2 BLENDED LEARNING INTERACTION AND INTEGRATION IN A MOBILE ENVIRONMENT FOR UNIVERSITY STUDENTS

Group dynamics theory highlights the significance of collective learning objectives for student group formation and stability in mobile learning environments. Through online interactions, student groups often develop shared learning objectives that underpin ongoing group interactions and drive learning activities. These common objectives provide clear direction for the group, influencing individual and collective decision-making. However, traditional methods for identifying learning objectives tend to focus on aggregating individual preferences, which may not accurately reflect the group's collective aims, thus potentially reducing learning efficiency.

To address this, the study introduces a graph structure to represent interaction data within the mobile learning environment, modeling various interactions as nodes and edges for a clear depiction of relationships among students, resources, peers, and teachers. Utilizing graph representation learning techniques from deep learning, the study generates comprehensive representations of each learning group, capturing the nuances of group interactions.

Additionally, an adaptive fusion mechanism is employed to integrate multi-source learning experience data effectively. This method not only improves the model's capability to represent diverse learning experiences but also links individual experiences with group objectives, ensuring that personal learning aligns with group goals. This approach effectively supports the blended learning process for university students in a mobile environment.

2.1 Representation learning of blended learning experiences at the interaction group level

The representation of blended learning experiences at the group level requires a comprehensive analysis and modeling of the interaction behaviors within the group, the relationships among members, and the evolving characteristics of the group throughout the learning process. In a mobile learning environment, the interactions within learning groups not only include traditional teacher-student interaction and peer collaboration but also involve various forms of communication, such as instant messaging via mobile devices, online collaboration, and the sharing and feedback of learning resources. These interaction behaviors reflect not only the learning dynamics within the group but also the overall cognitive tendencies of the group. Therefore, in representing learning experiences, it is necessary to analyze individual learning data and model the interaction patterns within and between student groups to capture the overall characteristics of group learning experiences.

To achieve this, a graph structure was proposed in this study to encode interaction data from blended learning in a mobile environment and to construct a representation model of the learning groups. By mapping interaction behaviors within the group as nodes and edges in the graph structure, the structural characteristics and dynamic relationships of the group can be more effectively represented. Each node can represent a student or a learning resource, while the edges reflect different types of interactions, such as information sharing, collaborative learning, or feedback. Using deep learning-based graph representation learning methods, group-level feature representations can be extracted from different interaction patterns. Figure 1 illustrates an example of interaction group-level blended learning modeling.

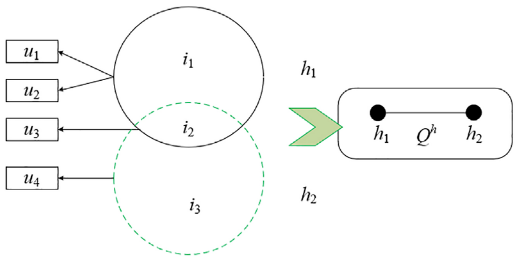

Fig. 1. An example of interaction group-level blended learning modelling

Firstly, a weighted graph model was constructed to describe the relationships among interaction groups. In a mobile learning environment, different learning groups may share certain members, and these shared members act as bridges for information dissemination, resource sharing, and collaborative interaction between the groups. Based on this interaction feature, each learning group, denoted as h, was considered a node in the weighted graph H^h. If there is at least one shared member between two groups, a weighted edge is established between the corresponding nodes. The weight of the edge reflects the degree of member sharing between the groups; the greater the number of shared members, the closer the connection between the groups, and the higher the edge weight. This member-sharing-based weighted graph structure more accurately captures the potential pathways for the transmission of learning resources and knowledge between groups. Let N^h represent the nodes in the weighted graph H^h and R^h represent the edges in H^h. If groups h_o and h_w share the same nodes, they are connected by an edge. The following equation expresses the weighted graph H^h:

$$H^h = (N^h, R^h, Q^h) \tag{1}$$

Assuming the number of shared members between groups h_o and h_w is represented by $|h_o \cap h_w|$, the total number of members in these groups is denoted by $|h_o \cap h_w|$, and the number of learning resources shared by the common members of these groups is represented by $|c_o \cap hc_w|$. The total number of learning resources shared by all students in these groups is also denoted by $|c_o \cap hc_w|$. The weight of the edge in the weighted graph H^h is denoted by Q^h, and the weight $Q^h_{(o,w)}$ of the edge (h_o, h_w) is calculated using the following formula:

$$Q^h_{(o,w)} = \frac{|h_o \cap h_w| + |c_o \cap c_w|}{|h_o \cup h_w| + |c_o \cup c_w|} \tag{2}$$

After constructing the weighted graph H^h, graph neural networks (GNNs) were employed to perform representation learning of blended learning experiences at the interaction group level. The advantage of GNNs lies in their ability to learn higher-order features of nodes and their neighboring relationships in a graph structure, making them particularly suitable for capturing the complex relationships between groups. Each group h was first initialized as an f-dimensional embedding vector $H \in R^{j*f}$, where j denotes the number of groups and f represents the embedding dimension. This initial embedding can be generated based on the basic characteristics of the group or by using a pre-trained model for initialization. The initialized group embedding $H^{(0)} = H$ was then input into graph convolutional networks (GCNs). The core of graph convolution lies in utilizing the connections between groups to propagate and aggregate information. The following formula is used to average the convoluted embeddings, and the mean value $\hat{H}^h$ was taken as the final embedding result:

$$\hat{H}^h = \frac{1}{M+1} \sum_{m=0}^{M} H^{(m)} \tag{3}$$

The blended learning experience at the group level for the s-th group in group h can be obtained using the following equation:

$$\hat{h}^h_s = \hat{H}^h(s,:) \tag{4}$$

The final group embedding $\hat{H}^h$ can be applied to various subsequent tasks, including the prediction of group learning objectives, the evaluation of learning outcomes, and the analysis of group behavior patterns. By training the GNNs, the model parameters can be continuously optimized, improving the model's ability to capture the complex relationships between learning groups.

2.2 Representation learning of blended learning experiences at the group member level

In a mobile learning environment, interactions between students are multidimensional and not limited to pairwise individual interactions. There are often complex multi-party interaction scenarios. For instance, a student may simultaneously participate in multiple learning groups, where these groups may have overlapping members, interrelated learning tasks, or even shared learning objectives. In such cases, representation learning based solely on pairwise interactions is insufficient to capture the full complexity of the relationship network among students. Traditional graph models, such as weighted graphs, can effectively depict one-to-one or one-to-many relationships between members, but they fall short in expressing higher-order information found in multi-party interactions. This higher-order information is critical for understanding how group members collaborate, influence each other, and collectively promote the evolution of blended learning experiences. Therefore, adopting a hypergraph model for higher-order interaction modeling is better suited for capturing the intricate interaction patterns between members, providing a more accurate data structure for subsequent representation learning. Moreover, blended learning in a mobile environment involves a combination of online and offline learning modes, which often place a greater emphasis on individual active participation and collaborative learning. The learning experience of an individual is influenced by interactions with other members within the group, particularly in terms of psychological perception, social relationships, and cognitive interplays.

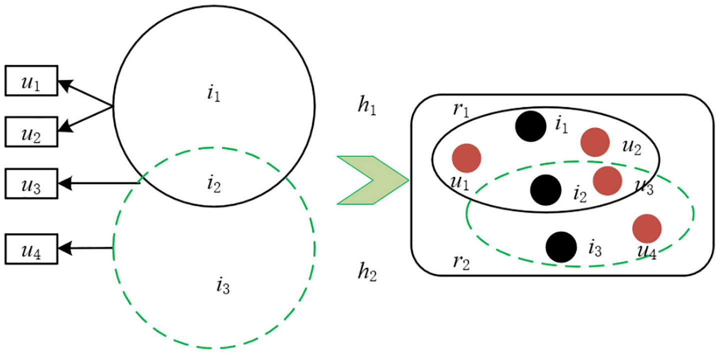

Fig. 2. Interaction data modeling in blended learning at the group level

These factors collectively drive the evolution of the group's blended learning experience. Modeling and representing these interactions at the member level can more precisely reveal the underlying mechanisms of these interactions. Figure 2 provides an example of interaction data modeling at the group member level in blended learning.

In a blended learning environment supported by mobile interactive technology, group interaction not only involves collaboration among members but also includes the publishing and sharing of learning resources by members. Therefore, a hypergraph was first constructed in this study to capture higher-order interactions that include member nodes and learning resource nodes, providing a comprehensive representation of the relationships between interaction groups, members, and learning resources. Specifically, the nodes representing members and resources, along with their interactions, are connected through hyperedges, forming a hypergraph that reflects higher-order information. The construction of hyperedges allows for the representation of scenarios where different members share resources or engage in multi-party collaboration, laying the foundation for interaction modeling at the member level. Let N^l represent the hypernodes, R^l represent the hyperedges, and G^l represent the adjacency matrix of the hypergraph. The hypergraph of member-level interactions can be expressed as follows:

$$H^m = (N^l, R^l, G^l) \tag{5}$$

In this way, higher-order interactions among members in the blended learning environment were effectively mapped onto a hypergraph structure, establishing the foundation for subsequent representation learning based on hypergraph neural networks (HGNNs).

Representation learning based on HGNNs has been shown to offer significant advantages in terms of fairness, efficiency, and expressiveness. Therefore, this method was chosen for representing blended learning experiences at the group member level in this study. Let $XHH_{NO}()$ represent the node aggregation function, Lr denote the set of members, and i_t be the embedding of the t-th student. The aggregated blended learning experience for the members can be calculated using the following equation:

$$l_{r,i} = XHH_{NO}\left(\left\{ i_t \mid i_t \in Lr \right\}\right) \tag{6}$$

Assuming the embedding of the k-th learning resource is denoted by u_k, and the set of interactions where students publish learning resources is represented by Ar, the aggregated blended learning experience for the learning resources can be calculated using the following equation:

$$l_{r,u} = XHH_{NO}\left(\left\{ u_k \mid u_k \in Ar \right\}\right) \tag{7}$$

A linear transformation was applied to fuse the aggregated blended learning experiences of both the students and the learning resources on the hyperedge, as shown below:

$$l_r = concat(l_{r,i}, l_{r,u}, l_{r,u} \Phi h_r) Q^d \tag{8}$$

Let the hyperedge aggregation function be represented by $XHH_{gr}()$, and let R_k denote the set of hyperedges related to node u_k. The refined node embedding for the target learning resource node u_k is updated using the following formula:

$$\hat{u}_k = XHH_{gr}\left(\left\{ l_r \mid r \in R_k \right\}\right) \tag{9}$$

Assuming the number of convolution layers is represented by M, and the embedding of node u_k at the m-th layer is denoted by $u_k^{(m)}$, the final representation of node u_k is generated by averaging the node embeddings obtained from each layer, as follows:

$$\hat{u}_k = \frac{1}{M+1} \sum_{m=0}^{M} u_k^{(m)} \tag{10}$$

By averaging the aggregated blended learning experience information over M convolutional layers and assuming the blended learning experience information contained in group r at the m-th layer is represented by $l_r^{(m)}$, the final blended learning experience information at the group member level is obtained as follows:

$$\hat{h}_r^l = \frac{1}{M+1} \sum_{0}^{M} l_r^{(m)} \tag{11}$$

2.3 Adaptive integration of blended learning experiences

To achieve adaptive integration of learning experiences across resources, groups, and members, a weight allocation mechanism was introduced in this study. The key to this integration lies in dynamically adjusting the integration weights of different levels of representations based on specific learning contexts and interaction behaviors. Specifically, when members within a group collaborate closely, the group-level experience representation $\hat{H}^h$ may contribute more significantly to the overall experience, and its weight will increase accordingly. If certain learning resources have a critical impact on the learning of group members, the weight of the resource-level experience representation $\hat{H}^u$ can be elevated. In some scenarios, the dominant learning behavior of individual members may have a greater influence on the overall learning objective, in which case the member-level experience representation $\hat{H}^l$ may assume a more prominent role. The expression for the blended learning experience is as follows:

$$\hat{H} = \beta \hat{H}^u + \alpha \hat{H}^h + \sigma \hat{H}^l \tag{12}$$

Through this dynamic weight adjustment mechanism, the system can flexibly and adaptively adjust the integration of experience representations at different levels according to real-time interactions within the student group. This ensures that the integrated representation accurately reflects the learning objectives of the group.

3 GROUP LEARNING OBJECTIVES AND STRATIFICATION FOR UNIVERSITY STUDENTS IN A MOBILE ENVIRONMENT

Based on the fusion of multi-source learning experiences, the shared learning objectives of the group were identified in this study by analyzing their preferences and evaluations of learning resources. This process can be likened to the formation of group consensus, where the learning resource with the highest score in the group is identified as the shared learning objective. By using the integrated multi-source experience representation, preference scores for each student regarding different learning resources can be calculated. These preference scores reflect the subjective feelings and evaluations of the students when using the resources. By aggregating the preference scores of all group members, an overall evaluation of each learning resource can be derived for the group. The learning resource with the highest preference score is then selected as the group's shared learning objective. This process is similar to the "optimal resource recommendation" found in recommendation systems, where the most widely accepted resource is determined based on the group members' use of learning resources. The identification of the target learning resource helps consolidate individual needs into a unified learning objective, thereby optimizing the group's learning outcomes. Specifically, assuming that the group's perceived preference for learning resources is represented by $\dot{b}_{s,k}$, a function with input dimension f and output dimension 1 is denoted by $MLP()$. The final blended learning experience representation of group h_s is represented by $\hat{h}_s$, while the refined embedding of the learning resource u_k is denoted by $\hat{u}_k$. The interaction between the two matrices is represented by $\hat{h}_s \Phi \hat{u}_k$, and the group's score for the learning resource is calculated using the following formula:

$$b_{s,k} = MLP\left(\hat{h}_s \Phi \hat{u}_k\right) \tag{13}$$

The calculation of semantic similarity was implemented using natural language processing techniques, primarily to measure the proximity between the learning resources used by each student and the target learning resources. If the resources used by a student exhibit high semantic similarity with the target learning resources, it indicates that the student's learning needs and habits are closely aligned with the group's objectives. Conversely, a lower similarity suggests a divergence from the group's goals, reflecting the student's unique learning needs. Based on the semantic similarity results, students can be stratified into different levels. These levels not only reflect the proximity of the student to the group objectives but can also be further refined based on factors such as learning behavior and interaction patterns. The application of mental models helps in achieving more granular group stratification by analyzing students' cognitive levels, learning strategies, and psychological states. The specific steps are as follows:

Step 1: Semantic vectorization of learning resources: This step involves converting the blended learning resources used by students in a mobile learning environment into numerical feature vectors suitable for computation. Since the learning resources are expressed primarily in natural language, they are not directly suitable for semantic similarity calculation. Therefore, Word2Vec technology was applied to convert these learning resources into vectors. In this study, the Continuous Bag of Words (CBOW) method within the Word2Vec model was used, and the implementation steps are as follows:

a) All learning resources were tokenized, and stop words were removed to ensure that the final vocabulary used for training consists only of the key content words in the learning resources. This can reduce noise and improve the semantic accuracy of the word embedding model.
b) The CBOW method was employed for word embedding training. CBOW predicts the target word using its surrounding context words, making it well-suited for modeling learning resources with concentrated semantics. During training, each word was mapped into a low-dimensional vector space, where semantically similar words were positioned close to one another. The window size was set to 5 in this study to effectively capture the contextual semantic information.
c) Using the trained Word2Vec model, the word vectors for each learning resource were averaged to obtain an overall semantic vector representation of the resource. This vector not only encapsulates the semantic information of the learning resource but also preserves its structural characteristics, laying the foundation for subsequent semantic similarity calculations.

Step 2: Vectorization of the student group learning objectives: Specifically, the learning objectives of a student group can usually be obtained by aggregating the frequently occurring learning resources within the group as follows:

a) Selection of shared learning objectives: First, the common learning resources within the group were identified, typically those that are used with high frequency by most students. These resources were considered as the group's shared learning objectives. To enhance representativeness, the semantic vectors of these high-frequency learning resources were averaged with weights to form a vector representation of the shared objectives.
b) Vectorization of learning objectives: Using the trained Word2Vec model, the group's shared learning objectives were converted into semantic vectors. Similar to the individual students' resource vectors, this group objective vector encapsulates the semantic information of the learning content, establishing a shared learning direction for the student group.

Step 3: Calculation of semantic similarity between student learning resources and group objectives: After vectorizing the learning resources, the cosine similarity formula was used to calculate the similarity between each student's learning resources and the group's shared learning objectives as follows:

a) Cosine similarity calculation: The similarity between each student's learning resources and the group's objectives was calculated using the following formula, where X represents the student's learning resource vector and Y represents the group objective vector. A higher cosine similarity indicates that the student's resource selection aligns more closely with the group's shared objectives, while a lower similarity suggests divergence from the group's objectives.

$$SIM = COS(\varphi) = \frac{X \times Y}{\|X\|\|Y\|} = \frac{\sum_{u=1}^{v} X_u \times Y_u}{\sqrt{\sum_{u=1}^{v} (X_u)^2} \times \sqrt{\sum_{u=m}^{v} (y_u)^2}} \tag{14}$$

b) Analysis of similarity distribution: The similarity scores between all students and the group's learning objectives were plotted to identify student groups across different ranges of similarity. Student groups with high similarity indicate a strong alignment with the group's learning objectives in terms of content selection, while those with lower similarity may exhibit more individualized learning needs or a stronger inclination towards exploratory learning.

4 EXPERIMENTAL RESULTS AND ANALYSIS

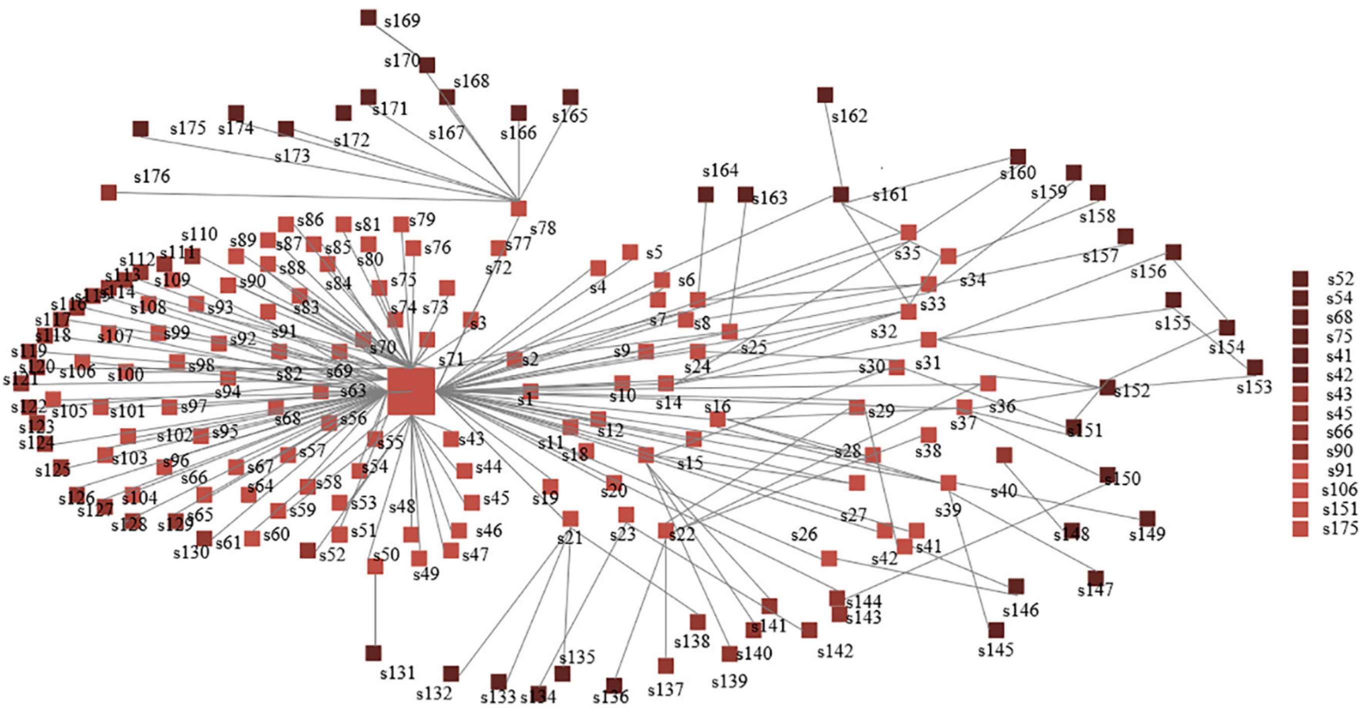

Fig. 3. Network graph of blended learning supported by mobile interactive technology

The multidimensional network structure of interaction patterns in blended learning within a mobile environment was revealed by constructing a relationship matrix. Specifically, data collected through mobile interactive technology was used to quantify the interactions between participants into matrix relations. The matrix format was then converted using UCINET software to ensure compatibility with UCINET and NETDRAW software. The transformed matrix was imported into NETDRAW to generate the network graph of blended learning supported by mobile interactive technology. The network graph in Figure 3 contains more than 180 nodes, each representing a teacher, teaching assistant, or student. The connections between nodes illustrate the interaction relationships among participants. The structure of the graph presents multiple densely connected sub-networks, which highlight the collaboration, resource-sharing, and communication pathways among different learning groups. This network graph provides a structured and visual representation of the interactions within the mobile learning environment, offering an insightful perspective on blended learning dynamics. Several conclusions can be drawn from analyzing this network graph. First, the densely connected sub-networks indicate that certain learning groups demonstrate a high frequency of collaboration and communication, which is often associated with students who have clear learning objectives and a high level of technological proficiency. These highly interactive groups are positioned as key nodes in the overall network, showing their central role in knowledge-sharing and resource circulation. Secondly, the presence of more isolated nodes or weakly connected groups suggests that some students have lower participation levels in blended learning supported by mobile interactive technology, potentially due to technical barriers or insufficient learning motivation.

Table 1. Stratification of university student groups based on differences in blended learning experiences

Stratification	Label	Basis for Division	Description	Learning Resources
Autonomous leaders	0	Semantic similarity in the range of (0.5, 1)	Aligns with mainstream experiences	21145
Collaborative active group	1	Semantic similarity in the range of (0.25, 0.5)	Trends consistent with mainstream experiences	56
Guided learners	2	Semantic similarity in the range of (–0.3, 0.25)	Oscillates between mainstream and new experiences	673
Passive recipients	3	Semantic similarity in the range of (–0.7, –0.3)	Opposes mainstream experience trends	14

Based on the data in Table 1, students were stratified into four levels through the classification of semantic similarity in blended learning experiences: autonomous leaders, the collaborative active group, guided learners, and passive recipients. The semantic similarity of the autonomous leaders ranges between (0.5, 1), with 21,145 students, indicating that their learning experiences closely align with the mainstream experience and they possess a wealth of learning resources. The collaborative active group has a similarity range of (0.25, 0.5), with only 56 students, whose experiences are consistent with the mainstream but form a smaller group. The guided learners, with a similarity range of (–0.3, 0.25), consist of 673 students, whose experiences oscillate between the mainstream and new learning experiences. Finally, the passive recipients group, with a similarity range of (–0.7, –0.3), has only 14 students, demonstrating experiences that diverge from the mainstream, with relatively low participation. Several conclusions can be drawn from these data. The majority of students fall into the autonomous leaders category, indicating that, in a mobile interactive technology-supported environment, most students align with mainstream blended learning experiences and make full use of available learning resources, exhibiting high levels of autonomy and leadership. The relatively small numbers of collaborative active groups and guided learners suggest that efforts are needed to further enhance their engagement and interaction frequency. Although the number of passive recipients is very small, their presence underscores that in any educational system, there may be some marginalized groups requiring additional attention and support. Overall, mobile interactive technology has had a significantly positive impact on the promotion and implementation of blended learning models in higher education, but differentiated support strategies are needed to ensure that all students achieve positive learning outcomes and experiences.

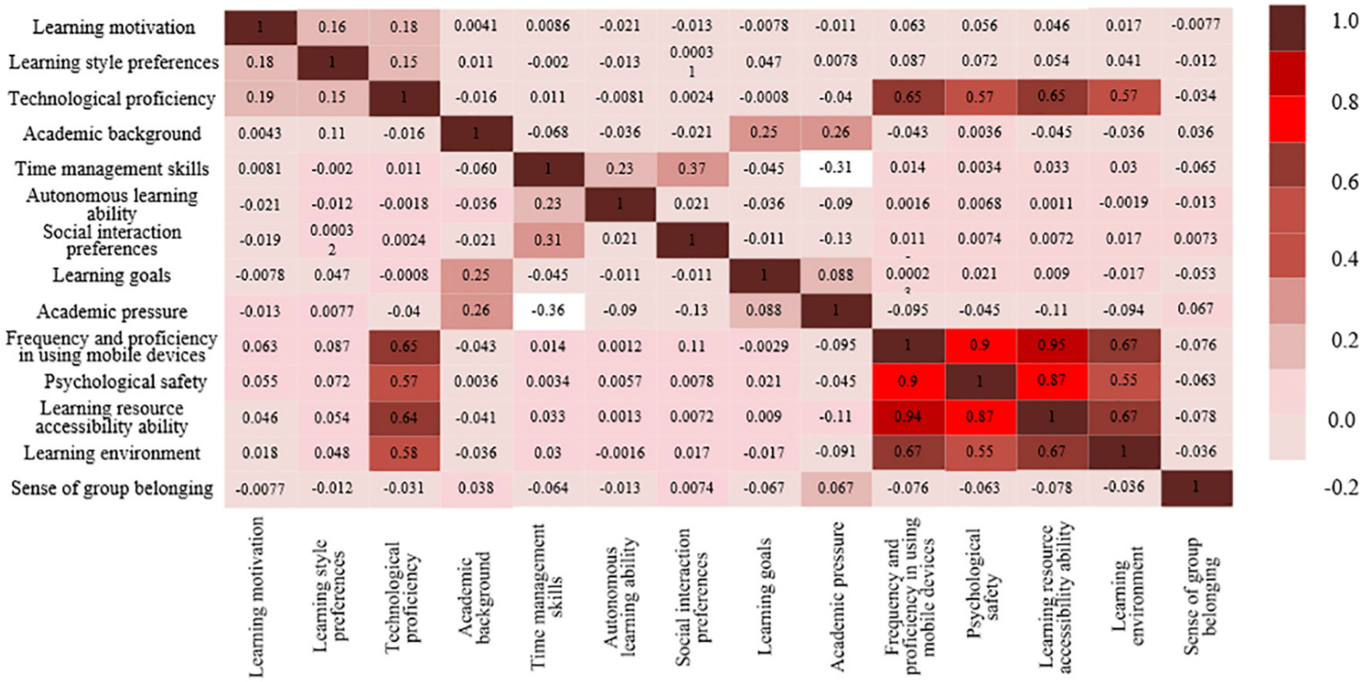

Fig. 4. Feature correlation analysis influencing the stratification of university student groups in a mobile blended learning environment

In this study, the experimental results were obtained through the feature engineering process in machine learning, where the raw data were preprocessed and effective features useful for task training were extracted. Specifically, the Pearson correlation coefficients between features and between features and labels were calculated, and a feature correlation visualization was generated, as shown in Figure 4. In the figure, the deeper the color in the intersecting areas of the horizontal and vertical axes, the stronger the correlation between them. According to the results of the feature correlation analysis, it was found that the correlation between features is relatively weak and has little influence on the classification outcomes. Therefore, no significant modifications were made to the feature set, and the original set was retained. This analysis ensures the scientific validity and effectiveness of feature selection, laying a solid foundation for the subsequent classification model. The feature correlation analysis also indicates that the various features involved in the blended learning experience within a mobile environment are relatively independent, with minimal influence on one another. This characteristic contributes to the model's ability to more accurately identify and classify the learning objectives of university student groups. The decision to retain the original feature set reflects that, for the blended learning model supported by mobile interactive technology in higher education, the existing feature extraction methods are already scientifically sound and comprehensive, effectively supporting the subsequent classification tasks.

Table 2. Classification results of university student groups in a mobile blended learning environment

Model	Precision (P)	Recall (R)	F1-Score
LR	0.9326	0.9562	0.9458
RF	0.9354	0.9236	0.9326
NB	0.9356	0.9234	0.9278
SVM	0.9341	0.9658	0.9489
Proposed method	0.9541	0.9741	0.9552

According to the data in Table 2, the precision, recall, and F1-scores of different models when classifying university student groups in a mobile blended learning environment are presented. The Logistic Regression (LR) model achieved a precision of 0.9326, a recall of 0.9562, and an F1-score of 0.9458. The Random Forest (RF) model had a precision of 0.9354, a recall of 0.9236, and an F1-score of 0.9326. The Naive Bayes (NB) model recorded a precision of 0.9356, a recall of 0.9234, and an F1-score of 0.9278. The Support Vector Machine (SVM) model attained a precision of 0.9341, a recall of 0.9658, and an F1-score of 0.9489. In comparison, the proposed method demonstrated the best performance, with a precision of 0.9541, a recall of 0.9741, and an F1-score of 0.9552, indicating higher accuracy and robustness in classification tasks. These results demonstrate that the introduction of mobile interactive technology in higher education can effectively enhance the understanding and analysis of students' blended learning experiences, facilitating the implementation of personalized education. The proposed method outperforms traditional machine learning models, particularly in terms of recall, meaning it is better at capturing the characteristics of different student groups. Through efficient identification and stratification of learning objectives, this method provides educators with a more comprehensive student profile, helping to explore personalized teaching strategies and resource allocation. This approach supports the further development of blended learning models in mobile environments. The data-driven stratification method provides a new technical pathway for improving teaching quality in higher education and highlights the importance of mobile interactive technology in education.

Based on Figure 5, it can be observed that the four groups (Group 0, Group 1, Group 2, and Group 3) exhibit varying feature contributions. In Group 0, the contribution of "learning motivation" is the highest, reaching 0.022, and features such as "autonomous learning ability," "learning style preferences," and "technological proficiency" also carry significant weight. This indicates that students in this group excel in autonomous learning and technological proficiency. In contrast, Group 3 also shows high contributions from "learning motivation" and "learning style preferences," but its overall feature contributions are more evenly distributed, with higher values particularly in "social interaction preferences" and "time management skills." This suggests that students in Group 3 may have a stronger inclination towards collaborative learning. Groups 2 and 1 show generally lower feature contributions, especially in features such as "learning goals" and "learning resource accessibility ability," reflecting that students in these groups may lack clarity in their learning objectives and have limited access to resources. Several important conclusions can be drawn from these data. First, students in Group 0 and Group 3 exhibit strong contributions in learning motivation, learning style, and social interaction, indicating that the mobile blended learning environment effectively stimulates these students' enthusiasm and preference for interaction. In contrast, students in Groups 2 and 1 perform weaker in these key features, suggesting that they may require additional support and guidance to enhance their engagement and resource accessibility. These findings highlight the need for differentiated support strategies in higher education when implementing mobile interactive technology-based blended learning models. For example, students with weaker autonomous learning abilities may benefit from more guided resources, while those with a higher preference for social interaction may require more opportunities for collaboration. These tailored approaches can ensure that all students fully benefit from the blended learning model.

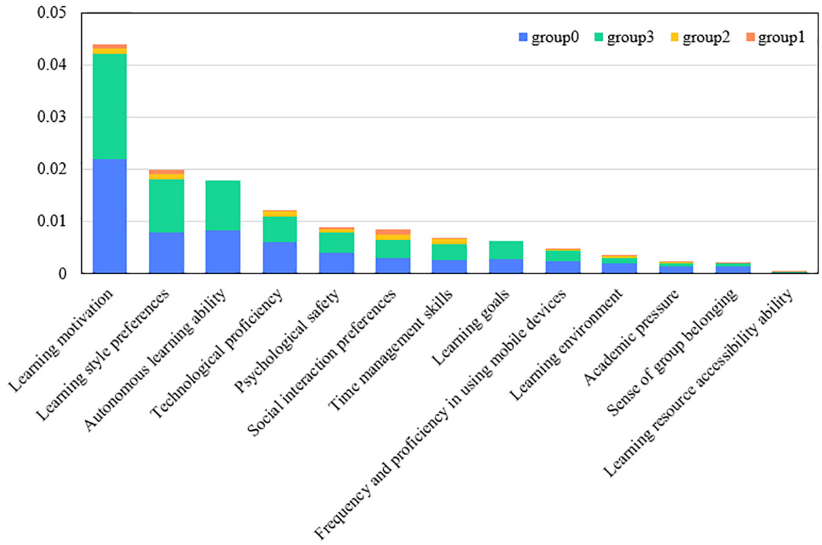

Fig. 5. Visualization of feature contributions to the classification of university student groups in a mobile blended learning environment

5 CONCLUSION

This study primarily investigated how to achieve the organic integration of university students' blended learning interaction models and blended learning experiences in a mobile environment, while exploring how mobile technology can be utilized to identify students' learning objectives and stratify student groups. The research covers the construction of blended learning network graphs, the parameter settings for identifying blended learning objectives, student group stratification based on differences in learning experiences, and the analysis of feature correlations and classification results. Various machine learning models (such as LR, RF, NB, and SVM) were compared for student group classification, and the proposed method demonstrated the best performance in terms of precision, recall, and F1-score. The experimental results also include a visualization of feature contributions to group stratification in a mobile learning environment, revealing significant differences in features such as learning motivation and social interaction preferences across different student groups.

This study has shown that mobile interactive technology effectively supports blended learning models in higher education and facilitates the implementation of personalized teaching. The proposed feature-based stratification method exhibits high accuracy, particularly in identifying students' learning objectives, highlighting its strong potential in this area. The analysis of feature contributions to group stratification reveals differences in learning motivation, autonomous learning ability, and social interaction across different groups, providing educators with a basis for developing targeted, personalized teaching strategies.

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7 AUTHOR

Ye Zhang, holds a master's degree from Tianjin Normal University and is currently employed at Shijiazhuang University of Applied Technology. Her primary research areas include Ideological and Political Education (E-mail: 2018010900@sjzpt.edu.cn; ORCID: https://orcid.org/0009-0001-3275-9826).