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PAPER

The Transformation of English Teaching Models and the Development of Intelligent Learning Environments in Higher Education Enabled by Mobile Technology

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ABSTRACT

With the rapid advancement of mobile technology, unprecedented opportunities for transformation have emerged in English teaching within higher education. The widespread adoption of mobile devices has extended the temporal and spatial dimensions of learning while significantly enriching the forms and content of teaching interaction. This evolution has driven a pedagogical shift from closed, linear models toward open, dynamic frameworks. Within this context, in-depth research on teaching interaction relationships under mobile-interactive environments has become critical for enhancing both teaching effectiveness and learner experience. Although previous studies have explored the design and implementation of mobile learning platforms, most have remained at a functional level, lacking quantitative analysis and structural identification of teaching interaction. Moreover, interaction data have primarily been processed using static methods, limiting the ability to dynamically capture authentic patterns and evolving trends in learner interaction. Therefore, a systematic research framework is urgently required—one capable of accurately identifying interaction relationships while translating analytical results into actionable strategies for pedagogical optimization and learning environment development. To address these needs, this study undertakes two core objectives: first, to identify teaching interaction relationships in mobile-interactive contexts by analyzing the structure, characteristics, and evolution of teacher-student and student-student interactions; second, to optimize English teaching models based on these findings and to construct an intelligent, personalized learning environment system. By leveraging data mining of mobile interaction relationships, a visualized and structured feedback mechanism was proposed for instructional practice, thereby promoting the development of English teaching in higher education toward a more intelligent, efficient, and interactive paradigm.

KEYWORDS

mobile technology, higher education, English teaching, interaction relationship identification, teaching model optimization, intelligent learning environment

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1 INTRODUCTION

With the rapid advancement of information technology, the application of mobile technology in the field of education has been progressively deepened, thereby driving the transformation of traditional teaching models in higher education—particularly in the context of English teaching [1, 2]. The widespread adoption of mobile devices, coupled with the continuous optimization of network infrastructure, has enabled learners to transcend temporal and spatial limitations, engaging in autonomous and flexible learning activities [3–7]. At the same time, mobile technology has provided diversified support for interaction within teaching processes [8, 9], significantly enriching communication channels between instructors and learners, as well as among learners themselves [10]. As a critical stage for cultivating high-quality talent [11], higher education must actively respond to the challenges and opportunities presented by emerging technologies by effectively integrating mobile technology into English teaching and realizing comprehensive innovations in instructional content, delivery methods, and learning environments.

Although growing attention has been directed toward teaching models and learning behavior analysis in mobile learning environments [12–16], significant gaps remain. For instance, Huang et al. [17] focused primarily on the functional design of instructional tools or platforms while overlooking the fundamental nature of teaching interaction. Other investigations have relied predominantly on subjective data collection methods such as questionnaires or interviews, lacking the capacity to dynamically capture and quantitatively analyze authentic interaction processes. Furthermore, most existing research has been limited to surface-level evaluations of teaching effectiveness. For example, Gómez et al. [18] and Heflin et al. [19] did not provide in-depth analysis of the structural features, interaction types, or evolutionary processes of interaction relationships. Such limitations have hindered the generation of precise evidence necessary for instructional optimization. Accordingly, there is an urgent need to establish a more systematic and scientifically grounded research framework—one that reveals the authentic dynamics of teaching interaction in mobile environments at a micro-level and that informs the subsequent optimization of teaching models.

Building upon the theme of "transformation of English teaching models and development of intelligent learning environments in higher education enabled by mobile technology," two primary areas of investigation were undertaken. First, teaching interaction relationships in higher education English teaching was identified within mobile-interactive environments, including an in-depth analysis of the structure, frequency, and influencing factors of both teacher-student and peer-to-peer interactions. Second, based on the identified interaction relationships, English teaching models were optimized, and a learning environment system supporting personalized and intelligent learning was designed and constructed. Through the integrated application of data mining, social network analysis, and educational technology design methodologies, this study aims to establish a new instructional paradigm that places interaction at its core and is supported by intelligent learning technologies, thereby providing a theoretical and practical framework to enhance teaching quality in higher education and to support the digital transformation of education.

2 IDENTIFICATION OF ENGLISH TEACHING INTERACTION RELATIONSHIPS IN HIGHER EDUCATION UNDER MOBILE-INTERACTIVE ENVIRONMENTS

2.1 Problem description

Traditional teaching models have typically been teacher-centered, with limited attention paid to the individualized needs of learners and the interactional characteristics of the learning process. With the advancement of mobile technology, teaching models have increasingly shifted toward student-centered approaches that emphasize interactivity and engagement. Within this emerging instructional paradigm, learners engage in real-time interaction with instructors and peers through mobile devices, enabling learning to extend beyond the physical classroom and rely more heavily on mobile platforms for support. Under such conditions, the identification of teaching interaction relationships has become essential for understanding the structural patterns of teacher-student and peer-to-peer interactions. This identification enables the revelation of latent interaction patterns, learning difficulties, and variations in engagement levels during the learning process, thereby providing data support for the further optimization of teaching models. A schematic representation of the various types of relationships within the mobile learning network is illustrated in Figure 1.

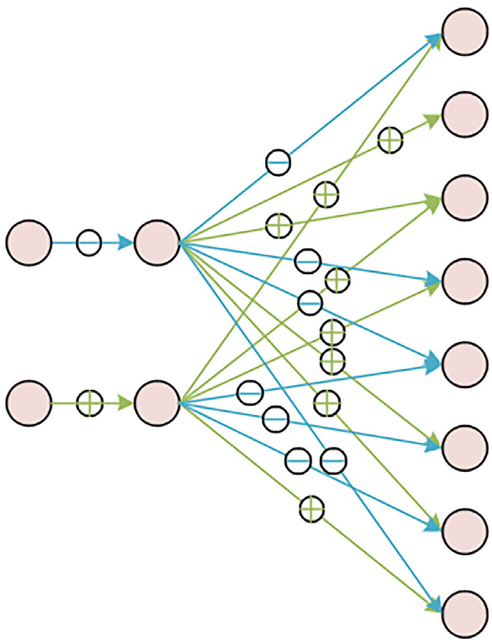

Fig. 1. Schematic representation of different relationship types within a mobile learning network

On the other hand, the construction of an intelligent learning environment must be grounded in a thorough analysis of teaching interaction relationships to enable personalized and precise learning support. Mobile-interactive environments provide rich data sources, including learning behaviors, interaction frequency, and affective feedback from learners. These data serve as a critical foundation for the development of intelligent learning systems. By identifying and analyzing interaction relationships, personalized learning pathways tailored to individual learners can be established, ensuring the adaptability and effectiveness of both instructional content and pedagogical strategies. Once interaction patterns have been identified through data mining techniques, instructional content and learning strategies can be dynamically adjusted within the intelligent learning environment. This allows learners to engage in a personalized and interactive context that optimizes their learning experience and outcomes. Furthermore, the identification and optimization of interaction relationships enhance instructors' real-time monitoring capabilities, enabling timely insights into students' progress and emotional states, which in turn supports more effective instructional implementation within intelligent learning environments.

In the context of identifying teaching interaction relationships in higher education English teaching under mobile-interactive conditions, network nodes were used to represent participants in instructional activities, such as teachers and students, or peer-to-peer interactions among students. Specifically, let $H = <N, R, T>$ denote a directed signed graph, where $N = \{n_0, n_1, \ldots, n_{V-1}\}$ represents the set of participants in English teaching, and $R = \{r_0, r_1, \ldots, r_{V-1}\}$ is the set of edges. The relationship between nodes can be positive or negative, and $T = \{+, -\}$ is the set of signs. A positive edge R^+ represents a constructive interaction, such as teacher encouragement or peer collaboration and support, whereas a negative edge R^- indicates a disruptive or adverse interaction, such as student resistance to instructional content or teacher dissatisfaction. Each edge's sign and type are encoded in an adjacency matrix X, where $x_{uk} = 1$ indicates a positive interaction between nodes n_u and n_k; $x_{uk} = -1$ indicates a negative interaction; and $x_{uk} = 0$ implies no direct interaction. Mobile-interactive networks dynamically capture evolving interaction behaviors between teachers and students, thereby revealing underlying interaction patterns within English teaching in higher education. The primary objective of this study is to infer the true sign of each interaction edge by analyzing relationships in mobile-interactive environments. More precisely, for any unmarked edge $r_j = (n_u, n_k)$, i.e., the interaction relationship between nodes n_u and n_k is unknown, the task is to determine its true sign $SIGN(r_u)$ based on existing information from known positive and negative edges.

2.2 Model construction

The proposed model for identifying English teaching interaction relationships in higher education under mobile-interactive environments comprises three key components: the embedding representation layer, the embedding propagation layer, and the relationship prediction layer. The model framework is illustrated in Figure 2. The embedding representation layer is designed to provide an initial embedding for each participant node in the instructional network. These embeddings capture the fundamental characteristics of each node and their preliminary relationships with other nodes, thereby facilitating the model's understanding of the relative position and functional role of each node within the higher education English teaching interaction network. The embedding propagation layer, constructed based on structural balance theory and status theory, serves to optimize the embedding representation of nodes and capture their interaction dynamics through a propagation mechanism. In this layer, the model incorporates inter-node interactions to iteratively adjust and propagate embeddings, thereby enhancing the representational capacity of each node. This process enables more accurate modeling of interaction relationships. The relationship prediction layer utilizes the optimized embeddings generated from the propagation layer to infer the types of unobserved edges. By learning from the types of those edges, the model can identify the interactive nature between teachers and students or among peers and continuously update and optimize the model parameters based on the predicted results.

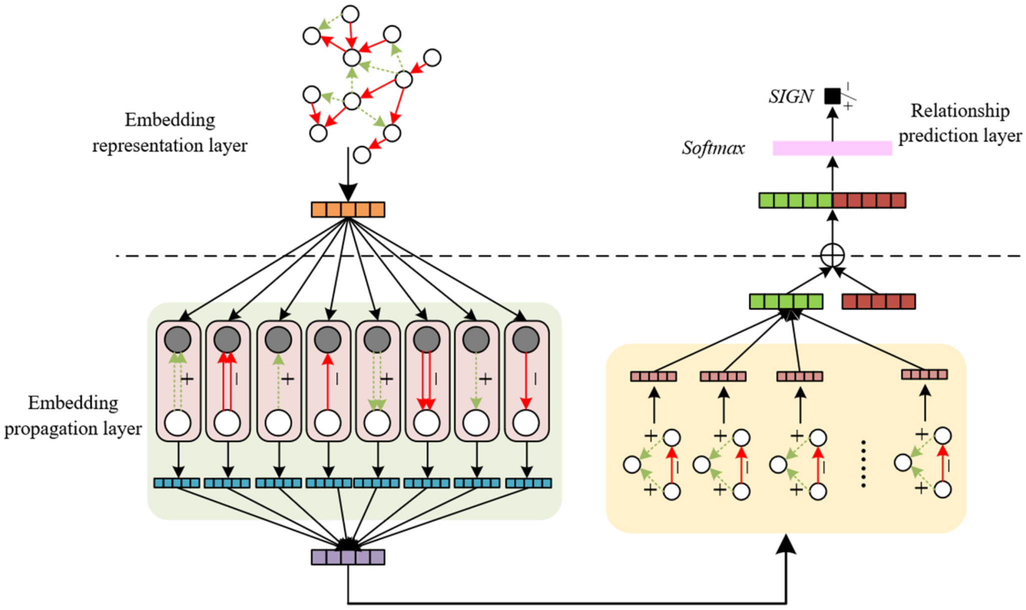

Fig. 2. Model framework for identifying English teaching interaction relationships in higher education under mobile-interactive environments

a) Embedding representation layer: The embedding representation layer is fundamentally designed to transform the features of each node into a low-dimensional embedding vector. The core objective of this transformation is to perform dimensionality reduction on complex, discrete input features, enabling their mapping into a more compact and computationally tractable space. Within the context of higher education English teaching, the initial input for each node is defined as a one-hot vector that encodes its basic attributes or identity information. For instance, the characteristics of an instructor may include the subject taught or teaching style, whereas the characteristics of a student may involve learning progress or level of engagement. By converting these discrete features into machine-processable binary vectors, a foundational basis is established for the subsequent computation of distances and similarity measures between nodes. Let the embedding vector of any given learner i be denoted as r_i, where the dimensionality of the embedding is represented by f. The embedding representation for each learner can thus be formally expressed as:

$$g = \left[o_{i_1}, o_{i_2}, o_{i_3}, \ldots, o_{i_f} \right] \tag{1}$$

In contrast to traditional graph neural network (GNN) approaches, the embedding representation layer in the present model does not simply transmit embeddings to hidden layers for final prediction. Instead, the embeddings are propagated across a signed network graph. These interactions—between instructors and students or among peers—may be either constructive and motivational or conflictual and adverse. Through the propagation of embeddings over the signed graph, the model is enabled to learn and reflect the dynamic variation in interaction relationships. As a result, each node's embedding representation not only encodes its intrinsic attributes but also captures the influence exerted by its interaction with other nodes.

b) Embedding propagation layer: The message-passing mechanism of the embedding propagation layer was designed based on the operational principles of GNNs, with the objective of effectively modeling inter-node relationships within higher education English teaching interaction networks. GNNs perform local convolution operations on a node's neighborhood to capture structural patterns in the graph. However, traditional graph convolutional networks exhibit limitations in handling directed edges and in assigning differentiated weights to neighboring nodes—challenges that are particularly pronounced in higher education English teaching interaction, where teacher-student and peer-to-peer relationships inherently carry different levels of importance and weights. To address these limitations, a graph attention network (GAT) was adopted in this study. Through the use of an attention mechanism, different learning weights were assigned to each neighboring node, enabling the model to focus more flexibly on neighbors with stronger relevance to teaching interactions.

Specifically, the message-passing mechanism optimizes node embeddings by cascading attention weights. A single-layer propagation process incorporates both edge attention and triplet attention. Edge attention focuses on the influence exerted by direct connections between nodes, while triplet attention further captures complex interaction patterns by considering triplets of nodes. In the context of higher education English teaching, interactions between teachers and students, as well as among students, are inherently multi-layered and multidimensional. Such complexity cannot be adequately modeled using conventional convolutional approaches. By employing a GAT, the model is enabled to capture subtle differences in node features and to adjust weights according to the actual interaction relationship of each edge, thereby improving the prediction accuracy. Specifically, for a given edge r_{uk}, its associated attention reflects the degree to which node u influences node k with respect to the interaction type. Assuming that the attention score is computed by a deep neural network denoted as $AT_{sio}(\cdot)$, the attention value for edge r_{uk} can be expressed as:

$$\tau_{uk} = AT_{sio}(g_u, g_k) \tag{2}$$

The edge attention mechanism fundamentally relies on edge attributes and adjacency relationships between nodes to assess the relative importance of different edges in identifying interaction types between nodes. Within mobile-interactive networks for higher education English teaching, the role of edge attention is particularly prominent—especially when modeling directed edges and signed relationships. For instance, the nature of teacher-student interactions may differ significantly from peer-to-peer interactions, and the sign of each edge carries distinct semantic implications. By adopting masked attention to compute attention over edges, the model is enabled to selectively focus on each node's relevant neighbors. This allows local interaction patterns to be effectively leveraged in evaluating the influence of each node on the identification of interaction types across the entire network. Let the activation function used in the deep learning framework be denoted by $\delta(\cdot)$, and this leads to:

$$\beta_{uk} = \text{softmax}(\tau_{uk}) = \frac{\exp\left(\delta\left(\omega^S \cdot \left[g_u \| g_k\right]\right)\right)}{\sum_{j \in V(u)} \exp\left(\delta\left(\omega^S \cdot \left[g_u \| g_k\right]\right)\right)} \tag{3}$$

The embedding of node u can be expressed as a function of the features of its neighboring nodes:

$$e_{uk} = \delta\left(\sum_{j \in V(u)} \beta_{uk} \cdot g_j\right) \tag{4}$$

In mobile-interactive networks of higher education English teaching, the interaction relationships between students and instructors, as well as among students, are inherently diverse and often characterized by signed attributes. To address this complexity, a triplet attention mechanism was introduced to enhance the model's capacity to distinguish among intricate interaction patterns. By performing nonlinear transformations on the embedding representations of triplets, the model is equipped to learn the structural characteristics of the triplet and to assign appropriate weights to each triplet structure. Specifically, a triplet $S_{ukj} = (n_u, n_k, n_j)$ is defined by the concatenation of the embedding representations of three associated edges, each representing the interaction between a pair of nodes. This representation enables the model to incorporate both direct relationships and higher-order interaction patterns that emerge through shared neighboring nodes. The embedding of the triplet $S_{ukj} = (n_u, n_k, n_j)$ can be formally defined as:

$$O_S = \{\tau_{uk}, \tau_{kj}, \tau_{ju}\} \tag{5}$$

The triplet attention mechanism further enhances the model by assigning different learning weights to each triplet, thereby allowing the model to adjust the influence of individual triplets during inference according to task-specific demands. For example, certain triplets may exhibit greater relevance in particular instructional scenarios, while others may play a more significant role under different conditions. This dynamic adjustment enables the model to selectively focus on varying types of teaching interactions, thereby improving identification accuracy. Let the deep neural network used for learning triplet attention be denoted by $AT_{seu}(\cdot)$. Then, the learned weight for a given triplet $S_{ukj} = (n_u, n_k, n_j)$ can be expressed as:

$$\rho_u = AT_{seu}(g_u, g_k, g_j) \tag{6}$$

A nonlinear transformation was then applied to the triplet embedding representation. Let the trainable parameters in the attention mechanism be denoted as Q_α and y_α. The learning weight can be formulated as:

$$\alpha_u = \frac{\exp(\rho_u)}{\sum_{j\in V(u)} \exp(\rho_u)} = \frac{\exp\left(q_\alpha^S \tanh(Q_\alpha g_S + y_\alpha)\right)}{\sum_{j\in V(u)} \exp\left(q_\alpha^S \tanh(Q_\alpha g_S + y_\alpha)\right)} \tag{7}$$

The final embedding representation of a given node is defined as:

$$W_u = \delta\left(\sum_{j\in V(u)} \alpha_u \cdot o_j\right) \tag{8}$$

c) Relationship prediction layer: In mobile-interactive networks for higher education English teaching, the embedding representation of each node captures not only individual user characteristics but also the nuances of interaction—such as instructional exchanges between teachers and students or collaboration and competition among students. Therefore, edge embedding representations derived through inner product operations can effectively reveal the relational features between nodes and support the classification of interaction types. Let the node embeddings for u and k be denoted by W_u and W_k, respectively. Assuming that the fully connected layer is represented by $d(\cdot)$, the embedding of the edge is given by:

$$b_{uk} = d(W_u \otimes W_k) \tag{9}$$

d) Model optimization: Interaction types among nodes in mobile-interactive teaching networks are inherently diverse and complex, encompassing relationships such as teacher-student teaching interactions and student-student collaboration or competition. To address this classification challenge, a cross-entropy loss function was adopted in this study. As a widely used and effective loss function for multi-class classification tasks, cross-entropy measures the divergence between true labels and predicted probability distributions, guiding model parameter optimization to minimize classification error. Let M denote the set of possible relationship types, and let | represent the size of this label set. The true relationship type of an edge r_{uk} is represented as $SIGN(r_{uk})$, while the predicted label produced by the model is denoted as b_{uk}. The objective function is defined as:

$$M = -\frac{1}{|M|}\sum_{t \in M}^{|M|} SIGN(r_{uk})\log(b_{uk}) \tag{10}$$

3 TEACHING MODEL OPTIMIZATION AND INTELLIGENT LEARNING ENVIRONMENT CONSTRUCTION BASED ON INTERACTION RELATIONSHIP IDENTIFICATION

By accurately identifying interaction relationships between students and instructors, as well as among students, the proposed model enables the revelation of in-class interaction patterns—such as student feedback to instructors, peer collaboration, and engagement with learning resources. These relationships serve not only as analytical tools for diagnosing instructional challenges but also as foundations for deeper understanding of the pedagogical process. For instance, if limited interaction is detected among certain student groups, this may indicate the need to revise instructional strategies—such as increasing group-based discussions or incorporating more interactive tasks—to promote collaboration. Based on such findings, instructional design can be dynamically adapted to better align with students' learning needs and instructional objectives, thereby facilitating the intelligent optimization of teaching models. Furthermore, instructional optimization can be achieved through the design of personalized learning pathways, driven by the results of interaction relationship identification. Learner engagement and learning outcomes can thus be enhanced. Within this framework, intelligent learning environments can autonomously generate individualized learning plans and task recommendations for each student based on the identified interaction patterns. For students who exhibit high levels of positive interaction, more challenging materials and tasks may be recommended to deepen their learning engagement. Conversely, students demonstrating low levels of interaction can be guided toward participating in collaborative activities, thereby improving their language skills through peer communication.

Through the precise identification of mobile-based teaching interactions, intelligent learning environments are enabled to dynamically adjust teaching resources and learning activities according to the detected interaction patterns. For example, the system can recommend personalized tasks, interaction content, and feedback mechanisms tailored to each student's learning pace and style. When low levels of teacher-student interaction are detected, additional instructor-led resources or discussion-based activities may be automatically provided to strengthen engagement. If peer interaction is found to be insufficient, collaborative tasks or discussion forums may be recommended to encourage student cooperation and communication, fostering active participation and improved learning outcomes. Moreover, the construction of intelligent learning environments extends beyond personalized resource recommendation;

it also requires the integration of diverse data sources for real-time analysis and feedback on learning status. Through deep analysis of interaction data, the system can monitor students' learning trajectories in real time and identify potential issues—such as lagging progress or declining motivation. In response, the learning environment can adaptively modify content difficulty, issue timely learning prompts, or adjust communication strategies based on emotional indicators to sustain student engagement. In this way, high-efficiency interaction can be continuously maintained throughout the teaching process, enabling the delivery of accurate and personalized learning support.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Description of datasets

Dataset	Coursera	Udemy	Blackboard
Number of participants (in 10,000)	10.265	26.235	76.235
Number of positive edges	135.264	248.248	384.235
Number of negative edges	42.128	45.236	118.236
Average number of nodes	32.6	21.8	12.6

Table 1 presents the characteristics of the datasets used in the experimental evaluation. The number of participants across the three platforms—Coursera, Udemy, and Blackboard—reached 102,650, 262,350, and 762,350, respectively. Compared to Coursera and Udemy, significantly more participants were observed on the Blackboard platform, which may reflect differing levels of platform adoption in various English teaching contexts. In addition to participant counts, the distribution of positive and negative edges across the platforms is also shown in Table 1. On Coursera, 135,264 positive edges and 42,128 negative edges were identified, indicating a dominant presence of constructive interactions. In contrast, the difference between positive and negative edge counts on Udemy and Blackboard was found to be relatively small, suggesting more complex interaction patterns. These platforms exhibited a higher proportion of bidirectional dynamics, where both supportive and adverse interactions coexisted among participants.

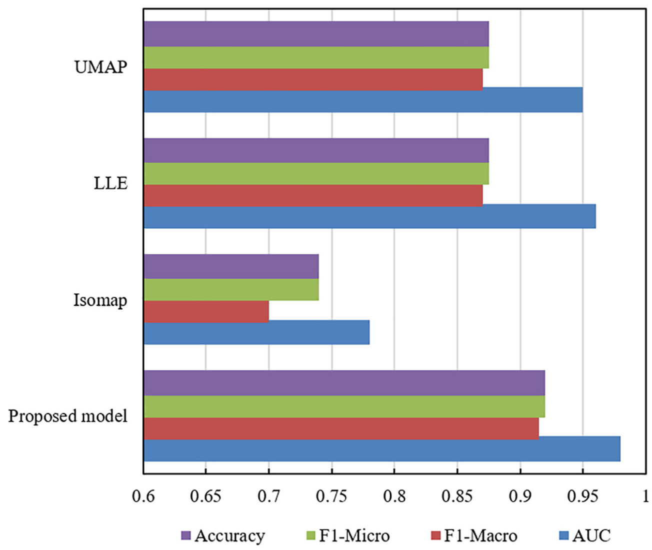

Fig. 3. Performance comparison of interaction relationship type identification on the Coursera dataset

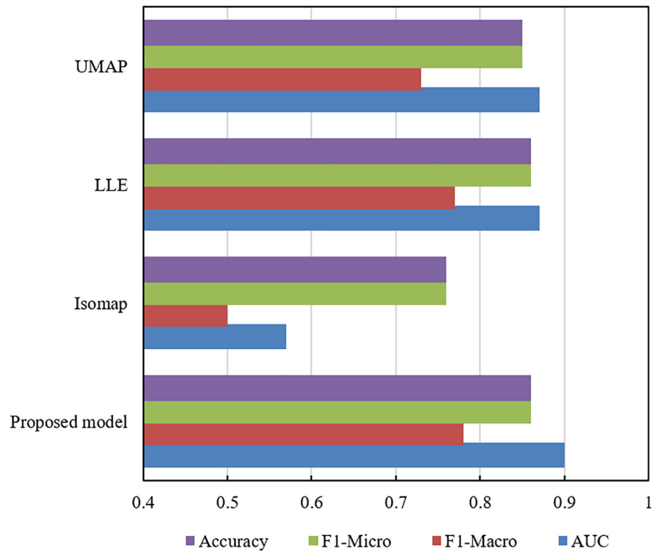

Fig. 4. Performance comparison of interaction relationship type identification on the Udemy dataset

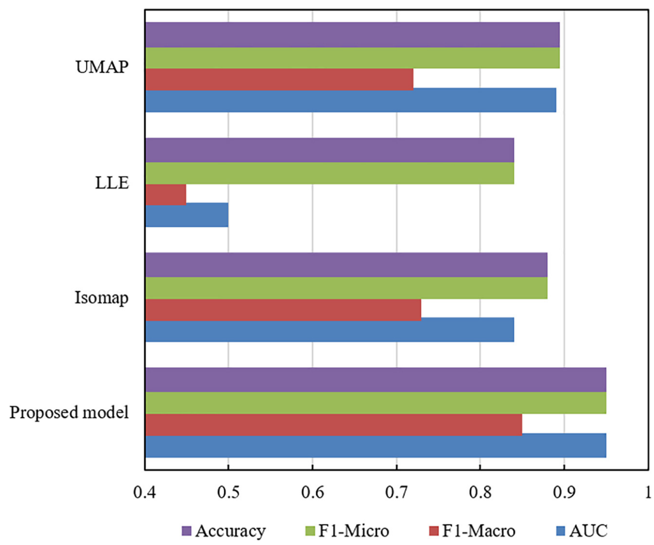

Fig. 5. Performance comparison of interaction relationship type identification on the Blackboard dataset

Further analysis of the experimental results shown in Figures 3 through 5 reveals that the proposed model consistently outperformed comparative methods across all datasets. On the Coursera dataset, the model achieved an Area Under the Curve (AUC) of 0.98, an F1-Macro score of 0.915, an F1-Micro score of 0.92, and an accuracy of 0.92. These results markedly surpassed those obtained by Isomap and Locally Linear Embedding (LLE), indicating superior classification performance and interaction relationship identification accuracy. In the case of the Udemy dataset, although the proposed model continued to exhibit competitive performance—with an AUC of 0.90 and an accuracy of 0.86—its F1-Macro (0.78) and F1-Micro (0.86) scores were observed to be closer to those of Isomap and LLE. This suggests that the model may encounter challenges when processing data on the Udemy platform, where the patterns of instructional engagement are more complex and harder to generalize. The results from the Blackboard dataset demonstrated the robustness of the model under high-complexity conditions. The model achieved an AUC of 0.95, an F1-Macro score of 0.85, an F1-Micro score of 0.95, and an accuracy of 0.95, all of which significantly exceeded the benchmarks established by Isomap and LLE. These results confirm the model's capacity to accurately process and differentiate between intricate interaction patterns—both teacher-student and peer-to-peer.

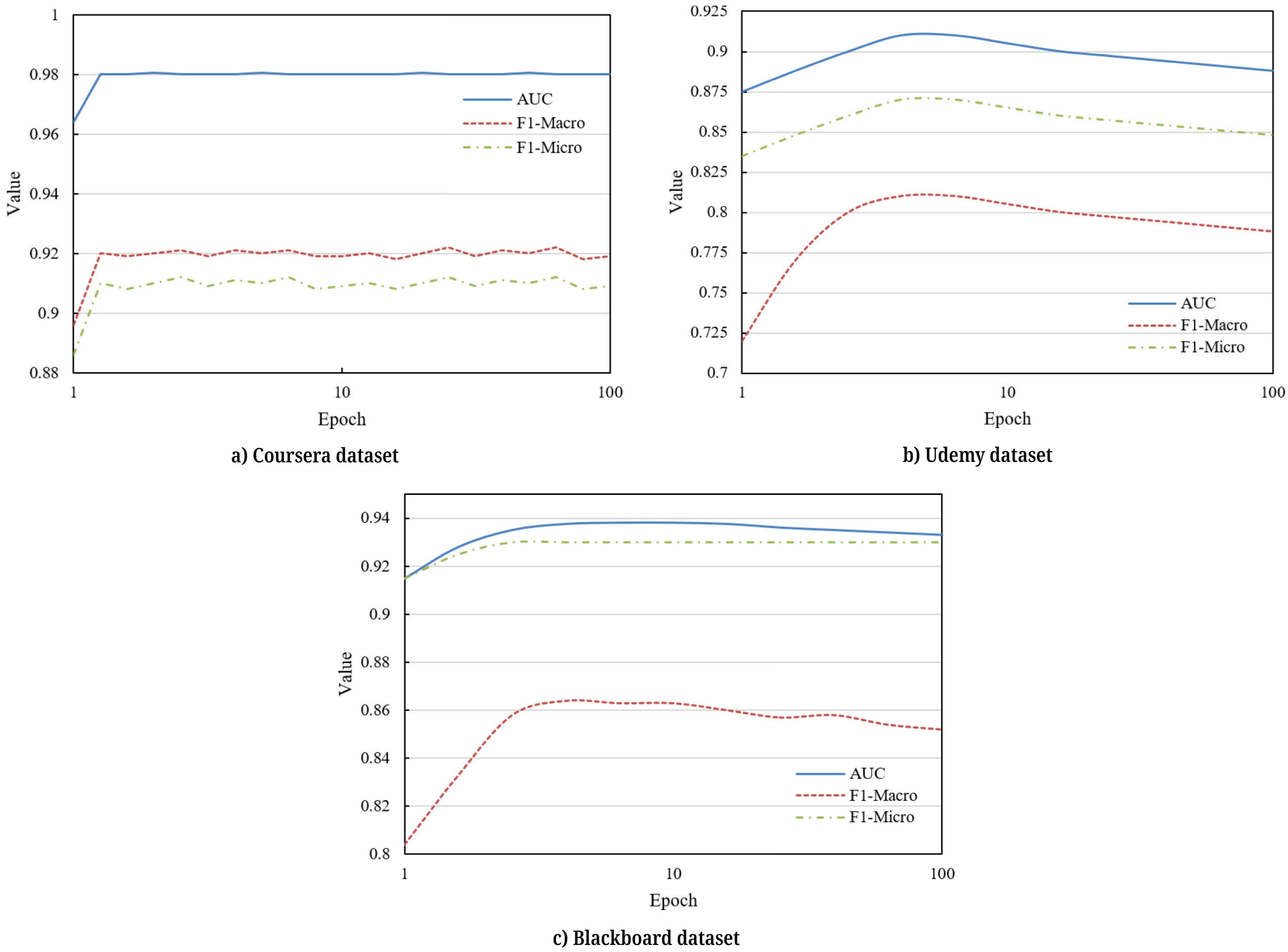

Fig. 6. Analysis of the epoch parameter across different datasets

Further analysis of the model's performance across different epoch values, as illustrated in Figure 6, reveals distinct behaviors on each dataset. On the Coursera dataset, model performance stabilized progressively as the number of epochs increased. The AUC remained consistently around 0.98, while both the F1-Macro and F1-Micro scores stabilized above 0.91. These results indicate that the model was able to efficiently identify and consistently preserve interaction relationship classification performance throughout the training process on the Coursera platform. For the Udemy dataset, at epoch 1, performance was relatively low, with an AUC of 0.875 and an F1-Macro of 0.72. However, with continued training, these metrics gradually increased, reaching 0.91 and 0.81, respectively, and stabilized at epoch 100. This suggests that the interaction patterns on Udemy are more complex and challenging to model, requiring a greater number of iterations for the model to learn effective representations. The Blackboard dataset demonstrated relatively stable behavior throughout the training process. At epoch 100, the model achieved an AUC of 0.935, an F1-Macro of 0.863, and an F1-Micro of 0.93, all indicating strong and consistent performance. These findings confirm that the proposed model is capable of adapting to and effectively optimizing interaction identification under complex and dense instructional structures.

The model's performance across varying epoch counts reflects a high degree of robustness and adaptability in identifying interaction relationships within mobile-interactive environments. Particularly on platforms such as Coursera and Blackboard—where interaction structures are more clearly defined—rapid convergence and stable accuracy were achieved, underscoring the model's strong application potential in intelligent learning environments. On the Udemy platform, although the model ultimately performed well, due to its complex interactive relationship structure, the training process of the model was relatively slow and may require more optimization to improve training efficiency. Overall, the progressive stabilization of performance metrics with increasing epochs confirms that the proposed model can effectively identify teacher-student and peer-to-peer interaction relationships in higher education English teaching, providing strong empirical support for the development of personalized and intelligent learning environments.

5 CONCLUSION

This study centers on the theme of "transformation of English teaching models and development of intelligent learning environments in higher education enabled by mobile technology," with two core areas of investigation. First, teaching interaction relationships within mobile-interactive environments were identified, with a particular focus on the structure, frequency, and influencing factors of teacher-student and peer-to-peer interactions in higher education English teaching. Through data analysis from multiple online platforms—including Coursera, Udemy, and Blackboard—distinct characteristics and variations in interaction relationships across platforms were revealed. The proposed model demonstrated superior performance compared to traditional approaches such as Isomap and LLE, particularly in identifying and optimizing interaction relationships and predicting their instructional influence. Enhanced classification accuracy and consistency were notably observed on the Coursera and Blackboard datasets. Second, teaching models were optimized based on the identified interaction relationships, and an intelligent learning environment system was designed to support personalized and intelligent learning, aiming to advance the innovation of English teaching models in higher education.

Despite these contributions, several limitations remain. Although strong performance was achieved across selected platforms, the generalizability of the model to a broader range of educational platforms and diverse instructional environments requires further validation. Additionally, the study was confined to the domain of English teaching. Broader applicability could be explored by extending the model to other subject areas, allowing for cross-disciplinary verification of its robustness. Furthermore, the adaptability of the model in real-time interactive contexts was not fully examined. Future investigations may consider the integration of real-time data streams to support dynamic adjustment and optimization of interaction relationships, thereby enhancing system responsiveness. Future research directions may include the following: (a) expanding the application scope of the interaction relationship identification model to explore its performance across disciplines and platforms; (b) enhancing model responsiveness and adaptability, particularly in mobile learning scenarios; (c) integrating advanced artificial intelligence technologies to further refine the intelligent recommendation capabilities of personalized learning systems for more accurate and efficient instructional support; and (d) incorporating comprehensive evaluation metrics—such as student satisfaction and learning outcomes—to further validate the teaching effectiveness of the optimized model to ensure the effectiveness and sustainability of the intelligent learning environment.

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