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PAPER

# Enhancing Student Engagement and Classroom Interaction through Mobile Interactive Technologies

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**ABSTRACT**

Under the framework of educational informatization, mobile interactive technology has emerged as a promising approach to address inefficiencies in traditional classroom interaction and the problem of low student engagement. However, current practices continue to face critical challenges, including the lack of personalized strategy design and insufficient recognition of implicit low-engagement patterns. Using the building information modeling (BIM) courses as a case study, it has been observed that while mobile collaboration tools improve the efficiency of complex knowledge interaction, issues such as lecture-dominated discourse and an overabundance of low-level interactions remain prevalent. Existing research has largely focused on optimizing application functionalities or evaluating explicit participation indicators, often neglecting deeper structural characteristics such as students' peripheral positions within interaction networks, sparse connectivity, and anomalies in interaction quality. Traditional graph models have been limited to direct connections and have failed to capture the potential for indirect collaboration through higher-order paths. Additionally, current deep learning approaches lack sufficient temporal modeling of dynamic interaction structures, resulting in strategy evaluation processes that remain empirically driven rather than data-driven. To address these limitations, a dynamic strategy evaluation method based on low-engagement graph link prediction was proposed. A heterogeneous graph model incorporating student, teacher, and resource nodes was constructed, supported by a subgraph extraction and line graph transformation algorithm to analyze multi-order indirect interaction paths. A tree-long short-term memory (LSTM) model was employed to aggregate edge features and generate embedded representations of interaction potential. Ranking loss training was utilized to address sample imbalance. This study transcends the limitations of explicit indicators by quantifying the structural characteristics of low-engagement students within the network. The proposed method provides data-driven support for the precise design of group collaboration suggestions and feedback optimization mechanisms on mobile platforms. A shift from "coarse-grained interaction" to "precision intervention" is thereby facilitated. These findings are expected to enhance the effectiveness of classroom interaction and contribute to greater equity in education.

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**KEYWORDS**
mobile interactive technology, student engagement, classroom interaction, graph link prediction, dynamic strategy evaluation

# 1 INTRODUCTION

As the integration of educational informatization deepens, the transformation of classroom interaction models has been recognized as a critical pathway for enhancing instructional effectiveness [1–3]. In the context of BIM courses, the inherent complexity of three-dimensional model manipulation and the spatial–temporal constraints of group collaboration in traditional classrooms have frequently led to passive learning behaviors. These have largely been attributed to the high participation threshold and limited interaction efficiency experienced by students [4, 5]. With the widespread adoption of mobile devices, technologies such as real-time model sharing [6], dynamic peer annotation and review [7], and mobile task delivery [8] have been gradually introduced. These tools have substantially improved both the comprehension of complex knowledge and the level of collaborative engagement. Nevertheless, challenges persist in current educational environments, notably the prevalence of monotonous interaction formats and insufficient depth of student participation [9, 10]. In particular, the design of personalized interaction strategies remains underdeveloped [11, 12], with limited capacity to identify students' latent participation patterns. The construction of an efficient interactive classroom ecosystem through mobile interactive technology—and the resolution of the imbalance between high technological investment and low participation output—has thus emerged as an urgent challenge within the field of educational technology.

Existing research on the use of mobile interactive technology to enhance classroom participation has primarily focused on strategy design from the perspective of tool application. These studies have typically aimed to optimize application functionalities in order to boost explicit participation indicators, such as click-through rates and speaking frequency [13, 14]. However, limited effort has been devoted to the in-depth analysis of the implicit behavioral patterns exhibited by low-engagement students. While some studies have utilized questionnaires and statistical methods to identify factors influencing participation [15], these approaches have proven inadequate in capturing deeper structural features, such as sparse connectivity of peripheral nodes and anomalies in interaction quality within classroom interaction networks. From a technical standpoint, traditional graph models have been restricted to direct node connections, thereby overlooking the latent potential for indirect interactions embedded in higher-order paths [16]. Concurrently, existing deep learning approaches have demonstrated insufficient capacity for modeling the temporal characteristics of dynamic interaction networks, making it difficult to evaluate the structural evolution of interactions following the implementation of a given strategy [17]. Furthermore, evaluations of mobile interactive strategies have largely remained at the level of user satisfaction, lacking systematic analysis grounded in network structure. As a result, strategy optimization has continued to rely on empirical judgment rather than data-driven evidence [18].

A mobile interactive strategy evaluation method based on graph link prediction was proposed in this study to address the issue of dynamic strategy optimization for low-engagement students. The scope of the study encompasses (a) the definition of heterogeneous symbols within mobile interaction networks, (b) the design of subgraph extraction and line graph transformation algorithms, (c) the construction of a tree-long short-term memory (LSTM) aggregation model, and (d) the development of a model training approach based on ranking loss. The core innovation lies in the deep integration of graph neural network techniques with educational scenarios, aiming to overcome the limitations of conventional strategies that rely solely on explicit participation indicators, thereby establishing a closed-loop framework comprising behavioral data collection, network feature modeling, and strategy effect prediction. By revealing the structural characteristics of low-engagement students within interaction networks, theoretical support was provided for the design of differentiated strategies on mobile interactive platforms. This advancement enables a shift from "coarse-grained interaction design" to "precision-based strategic intervention." The outcomes of this study are expected not only to enhance the effectiveness of classroom interaction but also to offer methodological references for interdisciplinary research in educational technology. Ultimately, the findings contribute to pedagogical innovation in the era of intelligent education.

## 2 DYNAMIC EVALUATION OF MOBILE INTERACTION STRATEGIES BASED ON LOW-ENGAGEMENT LINK PREDICTION

A dynamic evaluation method for mobile interactive strategies based on low-engagement graph link prediction was developed in this study, driven by the persistent challenge of identifying "latent low engagement" within classroom interaction networks. Certain students have exhibited sparse connectivity, pronounced peripheral positioning, and poor interaction quality—structural link characteristics that are inadequately captured by traditional evaluation methods. These latent behavioral patterns may influence the overall classroom interaction ecosystem. To address this issue, a mobile interaction network model was constructed in which students, instructors, and learning resources are abstracted as nodes, and interaction behaviors are represented as graph links. Through low-engagement graph link prediction, students exhibiting anomalous connectivity patterns can be identified. The effectiveness of current strategies in activating peripheral nodes, restoring broken interaction chains, and optimizing interaction link weights can thus be dynamically assessed.

The proposed graph link prediction methodology for low-engagement scenarios is grounded in the following principles. First, entities within the mobile interaction network, including students, instructors, and resources, are abstracted as nodes. Interaction behaviors such as questioning, collaboration, and resource access are represented as edges to form an initial graph model with node interaction features. Second, in order to isolate latent characteristics of low-engagement students, structural interaction data between node pairs are used to filter key nodes and edges. A subgraph with fewer nodes and edges is then constructed, capturing only the connectivity patterns associated with low engagement while removing irrelevant noise and strengthening core interactive features. Subsequently, this subgraph is transformed into a line graph structure, in which original edge features are redefined as nodes, and dependencies among those edges are encoded as new graph links. This transformation enables the propagation and aggregation of interaction features along inter-edge relationships. A tree-LSTM model is then applied for deep modeling of the resulting line graph. By aggregating the node features of the line graph layer by layer through a tree recursive neural network, anomalous connectivity patterns of low-engagement students in the interactive network, isolated nodes, broken temporal chains, and low-weight unidirectional links are captured. The output consists of embedded representations of node-pair relationships, enabling precise identification of graph link anomalies associated with low-engagement students.

### 2.1 Symbols

In the proposed low-engagement graph link prediction method, the graph is typically defined as $H = (N, R)$. The nodes of the mobile interaction network are defined based on entity attributes and interaction relationships. The node set $N$ comprises three primary entity types: a) Student nodes, denoted as $n_s$, represent individual learners. Their associated features include historical interaction frequency, temporal participation curves, and network position indicators relevant to low engagement, such as marginal connectivity. b) Teacher nodes, denoted as $n_t$, represent instructional facilitators. Key attributes include the frequency of interaction initiation and the responsiveness of feedback. c) Learning resource nodes, denoted as $n_r$, encompass course materials, discussion topics, task tickets, and related entities, with attributes such as resource access frequency and interaction depth. For any given node pair $(n_x, n_y)$, if both nodes are student nodes, the interaction represents student–student collaboration. If the pair consists of a student node and a teacher node, the interaction reflects student–teacher Q&A. If the pair consists of a student node and a resource node, the interaction reflects student–resource access. To support the detection of low engagement, core features of student nodes are centered on abnormal connectivity patterns within the interaction network, including degree centrality significantly below the group mean, a limited number of *j*-order paths to teachers or frequently interacting students, and a high proportion of unidirectional access edges to resource nodes. A subgraph $H^j_{x,y}$ was extracted by identifying multi-order paths between node pairs. Edges associated with low engagement—such as low-frequency collaboration edges or unidirectional notification reception edges—were transformed into nodes in a corresponding line graph $M(H^j_{x,y})$. The original features $a_u$ of these edges was preserved and enriched with interaction type, weight, and temporal attributes. These features serve as input for tree-LSTM-based aggregation to generate relational embeddings for node pairs, accurately capturing structural anomalies associated with low-engagement students within the interaction network, thereby providing a quantitative foundation for node definition to support dynamic strategy evaluation.

### 2.2 Subgraph extraction and line graph transformation

In mobile interaction networks aimed at low-engagement detection, multi-order paths between node pairs were defined as the set of indirect paths centered on a given student node pair $(n^x_s, n^y_s)$ within a maximum of $g$ hops, strictly excluding first-order direct edges. This exclusion is intended to prevent "information leakage" from direct interactions, which may obscure latent low-engagement behaviors. For example, when evaluating the interaction potential between Student $X$ and Student $Y$, relevant multi-order paths may include two-hop paths such as "$X \rightarrow$ Teacher $Z \rightarrow Y$," "$X \rightarrow$ Resource $F \rightarrow Y$," or a three-hop path such as "$X \rightarrow$ Group $E \rightarrow Y$." In the case of low-engagement students, multi-order paths typically exhibit sparse structural characteristics. Compared to highly engaged peers, significantly fewer indirect paths are found between low-engagement students and target node pairs. Moreover, the intermediary nodes in these paths tend to show low connection frequencies, and the overall edge weights across these paths are generally low. By focusing on these multi-order paths, the proposed method is capable of capturing the indirect connectivity weaknesses exhibited by low-engagement students within interaction networks—for example, passive participation patterns characterized by reliance on unidirectional content delivery from teachers rather than proactive collaboration. Figure 1 presents an illustrative example of a three-order subgraph structure.

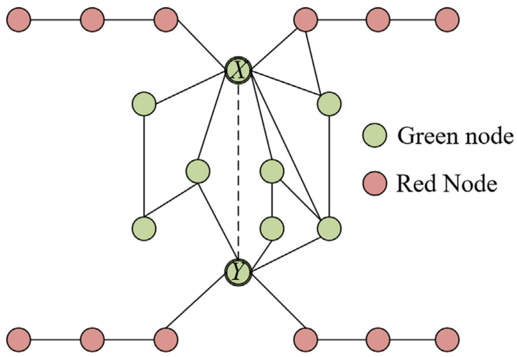


**Fig. 1.** Illustrative example of a three-order subgraph structure

The subgraph $H^{j}_{x,y}$, constructed from multi-order paths, was transformed into a directed line graph $M(H^{j}_{x,y})$ through a dual mapping mechanism: "edge-to-node" and "edge connection-to-edge relation." This transformation enables a structured analysis of interaction behavior chains. The process consists of the following steps: a) Edge node mapping. Each directed edge in the original path—for example, a question edge from Student $X$ to Teacher $Z$ or a feedback edge from Teacher $Z$ to Student $Y$—was transformed into an independent node within the line graph. The feature vector of each node was constructed by integrating the original edge attributes. For instance, a question–answer edge pair corresponds to two distinct nodes in the line graph, each carrying features such as "question complexity" and "response elaboration level." b) Edge relation construction. If two edges in the original path are sequentially connected (i.e., the tail of one edge is the head of the next), a directed edge is added between their corresponding nodes in the line graph. The direction is set from the predecessor node to the successor node, thereby modeling the temporal dependency and logical coherence of the interaction behavior. For low-engagement students, the corresponding line graph nodes are often characterized by unidirectional edge dominance and frequent breaks in the edge relation chain. Passive and fragmented participation processes can be clearly visualized in the line graph structure. Figure 2 presents an example of this line graph transformation.

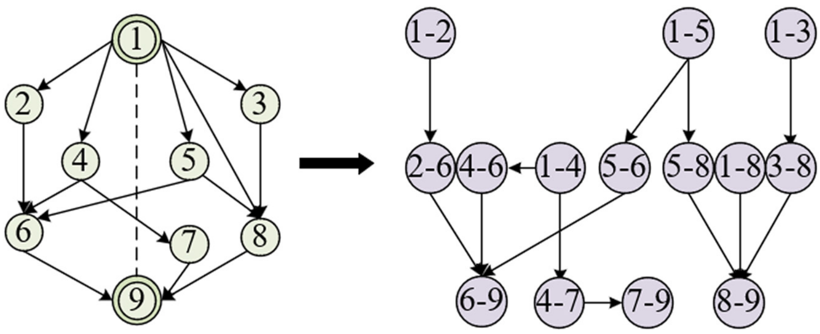


**Fig. 2.** Example of line graph transformation

### 2.3 Tree-LSTM aggregation model

In the proposed method for dynamic evaluation of mobile interaction strategies based on low-engagement graph link prediction, a tree-LSTM aggregation model was introduced in this study. The tree-LSTM model comprises two main structural variants: Child-sum tree-LSTM and N-ary tree-LSTM. Within the context of mobile interaction networks, the child-sum tree-LSTM structure has demonstrated distinct advantages for analyzing the interaction behaviors of low-engagement students. This structure aggregates the hidden representations of all child nodes through summation and uses the result as the input for computing the hidden state of the parent node, in accordance with the dependency relationships defined in the tree structure. This property is particularly critical in low-engagement link prediction tasks. For instance, when analyzing the interactions of Student *X* with other students, teachers, or learning resources, Student *X* may be regarded as the parent node, while the corresponding interaction nodes are treated as child nodes. By summing the hidden representations of these child nodes, a comprehensive measure of Student *X*'s position and influence within the broader interaction network can be derived. Additionally, the child-sum tree-LSTM incorporates a unique forget gate for each child node, allowing the model to selectively control the flow of information from each child to the target node. This mechanism proves especially effective in low-engagement scenarios, as it enables the filtering of irrelevant interaction signals—such as occasional ineffective clicks or brief periods of online presence without active participation—while preserving critical features indicative of low-engagement behavior. Let the set of child nodes of node $k$ be denoted as $Z(k)$. The transformation equation for the child-sum tree-LSTM is defined as follows:

$$\tilde{g}_k = \sum_{j \in Z(k)} g_j \tag{1}$$

Furthermore, let the sigmoid function be represented by $\delta$, and the node features in the line graph be denoted as $a_k$. The hidden state $\tilde{g}_k$ was used to compute the input gate $u_k$, forget gate $d_{jk}$, output gate $p_k$, and memory cell $z_k$:

$$u_k = \delta\left(Q^{(u)} a_k + I^{(u)} \tilde{g}_k + y^{(u)}\right) \tag{2}$$

$$p_k = \delta\left(Q^{(p)} a_k + I^{(p)} \tilde{g}_k + y^{(p)}\right) \tag{3}$$

$$i_k = \tanh\left(Q^{(i)} a_k + I^{(i)} \tilde{g}_k + y^{(i)}\right) \tag{4}$$

In the child-sum tree-LSTM architecture, a forget gate is assigned to each child node:

$$d_{kj} = \delta\left(Q^{(d)} a_k + I^{(d)} g_j + y^{(d)}\right) \tag{5}$$

Assuming that element-wise multiplication between matrices is denoted by ⊗, the final storage state is computed as:

$$z_k = u_k \otimes i_k + \sum_{j \in Z(k)} d_{kj} \otimes z_j \tag{6}$$

The updated hidden layer of the parent node $k$ can be obtained through:

$$g_k = p_k \otimes \tanh(z_k) \tag{7}$$

By contrast, the N-ary Tree-LSTM architecture is constrained to tree structures with at most $V$ branches, where child nodes are assumed to be ordered. Let the hidden state and memory cell of the $m$-th child node of parent node $k$ be denoted as $g_{km}$ and $z_{km}$, respectively. The following equations define the transformation rules for this structure:

$$u_k = \delta\left( Q^{(u)} a_k + \sum_{m=1}^{V} I_m^{(u)} g_{km} + y^{(u)} \right) \tag{8}$$

$$p_k = \delta\left( Q^{(p)} a_k + \sum_{m=1}^{V} I_m^{(p)} g_{km} + y^{(p)} \right) \tag{9}$$

$$i_k = \tanh\left( Q^{(i)} a_k + \sum_{m=1}^{V} I_m^{(i)} g_{km} + y^{(i)} \right) \tag{10}$$

$$d_{kj} = \delta\left( Q^{(d)} a_k + \sum_{m=1}^{V} I_m^{(i)} g_{km} + y^{(i)} \right) \tag{11}$$

$$z_k = u_k \otimes i_k + \sum_{m=1}^{V} d_{km} \otimes z_{km} \tag{12}$$

$$g_k = p_k \otimes \tanh(z_k) \tag{13}$$

In the directed line graph, relationships between parent-child node pairs are defined according to edge direction: the source node of the edge serves as the child node, and the target node is treated as the parent node. This directional structure aligns with the architectural characteristics of the Child-Sum Tree-LSTM, enabling the aggregation of information along the path direction of the directed line graph. Empirical results from link prediction experiments show that the model performs more effectively when $g$ is computed as the mean of the child node hidden states. By iteratively applying the Child-Sum Tree-LSTM model over the directed line graph for a fixed number of steps, information from nodes along each directed path is progressively aggregated toward the terminal node. In this context, RelpNet adopts the hidden representation of the terminal node of each path as the final representation of that path. The mean of all such path-level representations is then taken as the final representation of the entire line graph. Once this final graph representation is obtained, the link score between the target node pair can be computed directly using a linear equation. Accordingly, $\tilde{g}_k$ in the model was proposed to be redefined as:

$$\tilde{g}_k = \frac{1}{V} \sum_{j \in Z(k)} g_j \tag{14}$$

Let the representation of the $u$-th directed path be denoted as $g_{END_u}$, and let $V$ represent the total number of paths in the line graph. The final line graph representation $g_h$ is computed as:

$$g_h = \frac{1}{V} \sum_{u=1}^{V} g_{END_u} \tag{15}$$

Once $g_h$ is obtained, the link score for the target node pair can be calculated using:

$$t = Q_t \cdot g_h \tag{16}$$

## 2.4 Model training

To address the link characteristics of low-engagement students within mobile interaction networks, traditional binary classification methods have been found insufficient to accurately capture implicit patterns due to the extreme imbalance between positive and negative samples. As such, the training objective was reformulated as a ranking problem, requiring the model to assign higher scores to effective, real-world interaction links than to non-existent or inefficient ones. Specifically, a set of non-linked node pairs, denoted as $R^{-}$, was treated as negative samples. A loss function combining cross-entropy loss and L2 regularization was constructed. The former forces the model to maximize the score difference between positive and negative samples, while the latter constrains the parameter norm to prevent overfitting, thereby improving the model's generalization ability under sparse data conditions. During training, the model generates link scores based on multi-order path features from subgraph extraction, edge relationship representations derived from line graph transformation, and embedded node-pair vectors obtained through tree-LSTM aggregation. Optimization of the objective function enhances the model's ability to distinguish low-engagement-related negative samples. For instance, the prediction score of isolated student node pairs or unidirectional passive interaction edges is minimized relative to that of frequent collaborative node pairs or bidirectional effective interaction edges, providing a robust basis for ranking-oriented dynamic strategy evaluation. Let the RelpNet model be represented by $d_{\varphi}(\cdot)$, where $\varphi$ denotes the model parameters. The set of node pairs with no observed links in the known graph data is defined as $R^{-} = N \times N - R$. The L2 regularization term is given by $\eta/2\|\varphi\|^{2}$. The complete objective function is then expressed as:

$$\underset{\varphi}{MIN} \sum_{(n_u,n_k)\in R,(n_j,n_m)\in R^{-}} \left(1 - d_{\varphi}(n_u,n_k) + d_{\varphi}(n_k,n_m)\right)^2 + \frac{\eta}{2}\|\varphi\|^2 \tag{17}$$

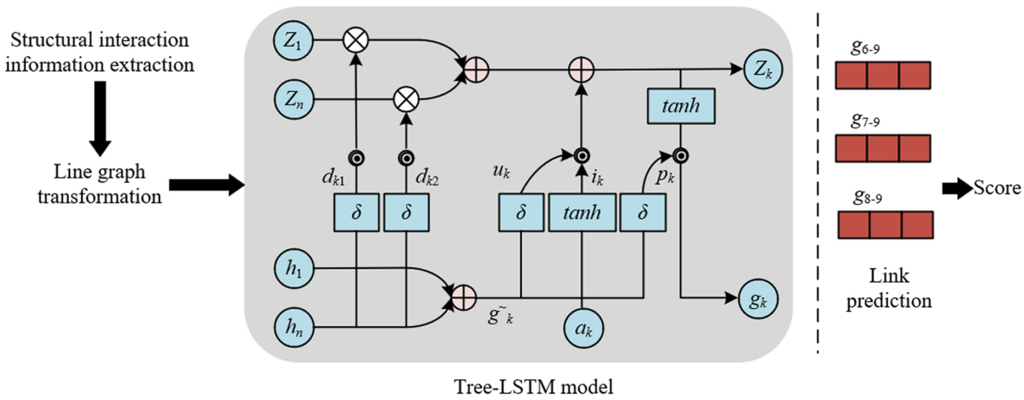


**Fig. 3.** Overview of the proposed prediction method

The overall training process is structured around four stages—balanced sample sampling, multi-order feature modeling, structured aggregation, and objective function optimization—to precisely capture abnormal interaction patterns associated with low-engagement students. First, a global sampling strategy was applied to construct the training dataset. A 1:1 ratio was used to sample from the set of actual links $E$ and the hypothesized non-link set $E^{\wedge -}$, alleviating the severe imbalance typically observed in mobile interaction networks, where valid interactions are sparse and potential non-links dominate. This ensures the model's sensitivity to negative samples associated with low engagement. Next, for each sampled node pair, a subgraph was extracted based on the definition of multi-order paths and transformed into a directed line graph. Features related to low engagement were encoded into the node and edge representations of this line graph. Then, the Child-Sum Tree-LSTM model was applied to aggregate node features along the directed paths. Through gated mechanisms, irrelevant noise was filtered, and key anomalous features were retained. Node-pair embeddings were generated, and link scores were computed, enabling patterns such as weak connectivity and asymmetric interaction—common among low-engagement students—to be distinguished from high-frequency interaction pairs. Finally, the objective function, consisting of a cross-entropy loss term and an L2 regularization term, was minimized as the optimization object. Model parameters were updated through iterative training until convergence was reached, resulting in a trained model capable of accurately detecting structural anomalies in the graph links of low-engagement students within mobile interaction networks. Figure 3 illustrates the full workflow of the proposed prediction method.

Upon the completion of low-engagement link detection, a closed-loop mechanism of detection–analysis–intervention–iteration was constructed to support mobile interaction strategy evaluation. First, structural deficiencies were precisely localized by detecting sparse static connectivity, broken multi-order paths, and anomalies in unidirectional interaction. These were quantified using the node-pair embeddings output by the tree-LSTM model, which reflect interaction potential. Based on the detection results, differentiated strategies were designed. For peripheral nodes exhibiting sparse connectivity, potential indirect paths to highly interactive students or core instructors were identified through subgraph extraction. Group tasks aligned with these paths were then selectively pushed to activate latent connections. For students demonstrating unidirectional interaction anomalies, mobile interface logic was adjusted to increase entry points for active engagement, and bidirectional interactions were initiated via instructor nodes.

## 3 EXPERIMENTAL RESULTS AND ANALYSIS

As shown in Table 1, the proposed method achieved the highest area under the curve (AUC) score of 96.32% in the static sparsity detection task, outperforming methods such as PathCount (93.65%) and SimRank (91.45%). This improvement reflects the method's superior ability to identify sparsely connected peripheral nodes. Such performance can be attributed to the modeling of heterogeneous symbols in mobile interaction networks and the integration of subgraph extraction with line graph transformation, which enabled effective structural relationship analysis. In the multi-order path disruption detection task, the proposed method achieved an AUC of 91.23%, surpassing large-scale information network embedding (LINE) (84.23%) and structural deep network embedding (SDNE) (75.63%). These results indicate that the integration of subgraph extraction, line graph transformation, and the Tree-LSTM aggregation model can effectively capture indirect multi-order path information and detect path discontinuity anomalies. In the unidirectional interaction anomaly detection task, an AUC of 91.23% was attained, exceeding that of probabilistic matrix factorization (PMF) (83.21%) and latent factor model (LFM) (75.59%). This outcome underscores the model's effectiveness in distinguishing unidirectional interaction patterns. The high performance is closely related to the ability of the tree-LSTM to aggregate node information and the use of ranking loss to enhance abnormal pattern recognition. Across additional tasks such as interaction frequency drop detection and cross-context interaction discontinuity detection, the proposed method consistently achieved leading performance. Notably, an AUC of 91.56% was achieved in Task 4 and 94.21% in Task 5, outperforming most baseline models.

**Table 1.** AUC scores (%) of different methods across detection tasks

| Methods | Task 1 | Task 2 | Task 3 | Task 4 | Task 5 | Task 6 | Task 7 |
|---|---|---|---|---|---|---|---|
| PathCount | 93.65 | 82.35 | 67.52 | 82.36 | 92.36 | 58.62 | 88.23 |
| SimRank | 91.45 | 77.51 | 67.61 | 82.54 | 88.54 | 58.41 | 88.41 |
| DeepWalk | 94.25 | 84.52 | 67.23 | 82.62 | 92.36 | 58.23 | 88.23 |
| LINE | 94.23 | 84.23 | 67.52 | 81.32 | 91.24 | 58.26 | 88.26 |
| SDNE | 92.58 | 75.63 | 73.26 | 81.26 | 92.36 | 57.41 | 84.52 |
| PMF | 81.26 | 75.21 | 83.21 | 88.69 | 77.89 | 74.26 | 94.23 |
| LFM | 83.26 | 81.26 | 75.59 | 78.95 | 88.62 | 58.62 | 92.54 |
| GraphSAGE-LinkPred | 94.52 | 87.23 | 85.41 | 91.56 | 93.54 | 77.58 | 95.68 |
| GAT-LinkPred | 95.68 | 91.25 | 86.26 | 92.25 | 94.26 | 82.23 | 96.52 |
| Proposed method | 96.32 | 91.23 | 91.23 | 91.56 | 94.21 | 81.23 | 95.26 |

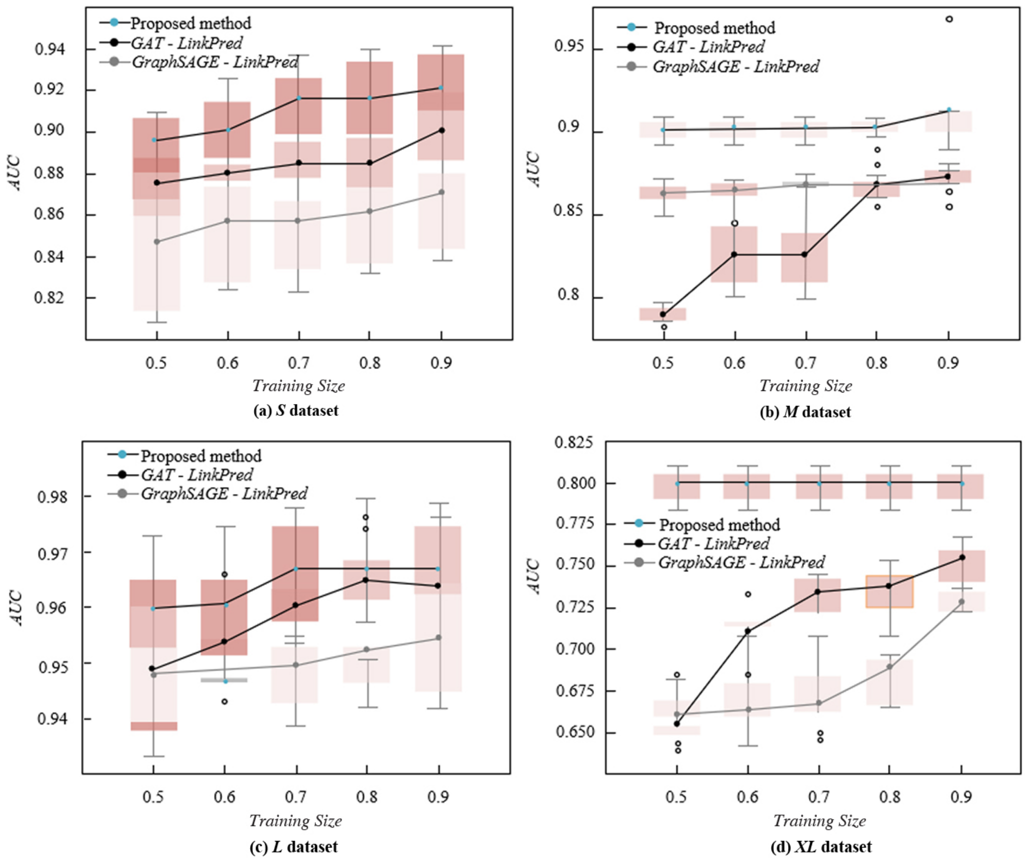


**Fig. 4.** Performance comparison of different methods across training sets of varying scales

According to the experimental results across datasets of varying scales in Figure 4, on the *S* dataset, a continuous increase in AUC was observed as the training size increased from 0.5, with performance consistently exceeding that of graph attention network for link prediction (GAT-LinkPred) and graph sample and aggregation for link prediction (GraphSAGE-LinkPred). Similar performance stability was observed on the *M* dataset, where the proposed method maintained a leading advantage across all training sizes. On the *L* dataset, the AUC achieved by the proposed method significantly outperformed all comparative methods, approaching a value of 0.98. Excellent performance was also maintained on the *XL* dataset. These results confirm that the proposed method is capable of accurately detecting low-engagement links regardless of training data scale, thereby providing robust support for subsequent mobile interaction strategy evaluation and interventions aimed at improving student engagement. The effectiveness, advancement, and strong generalization ability of the method in low-engagement link detection scenarios were thus validated.

As illustrated in Figure 5, the proposed method also exhibited strong AUC performance across all detection tasks under varying subgraph orders. In the static connectivity sparsity detection task, consistently high AUC values were achieved, indicating the method's effectiveness in identifying sparsely connected peripheral nodes. In the multi-order path disruption detection task, AUC values increased with higher subgraph orders, reflecting the model's ability—enabled by subgraph extraction, line graph transformation, and the tree-LSTM aggregation model—to effectively capture information embedded in higher-order indirect paths. Similarly, in the unidirectional interaction anomaly detection task and others, high AUC performance was maintained, demonstrating the method's ability to capture characteristic patterns of low engagement such as unidirectional interaction. Collectively, these experimental results confirm the method's effectiveness and structural adaptability in identifying various low-engagement link patterns.

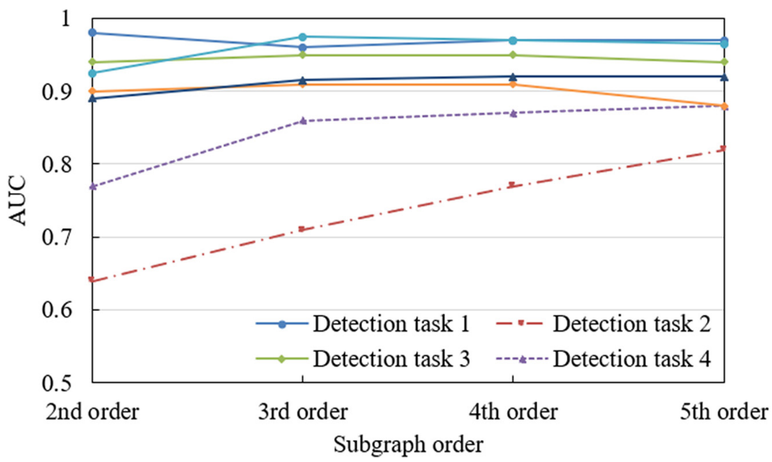


**Fig. 5.** Performance of the proposed method under different subgraph path orders

As reflected in Table 2, the average number of nodes and edges in both line graphs and subgraphs varies significantly across different low-engagement link detection tasks, demonstrating the task-specific adaptability of the proposed method. For instance, in Task 1 (static connectivity sparsity detection), the average number of nodes and edges in the line graph reached 115.23 and 158.32, respectively, while the subgraph contained 215.23 nodes and 1235.32 edges. These figures indicate that the subgraph extraction and line graph transformation algorithms effectively captured and integrated structural information relevant to sparsity conditions. In Task 2 (multi-order path disruption detection), the edge counts in the line graph (136.32) and subgraph (278.23) further validated the method's capacity to extract key path-related features under disrupted connectivity scenarios. Similarly, across the remaining tasks, the variability in node and edge counts confirmed that the method dynamically extracted information on nodes and edges based on the unique characteristics of each low-engagement pattern. This ensured that structured and task-relevant inputs were supplied to the tree-LSTM aggregation model. These results collectively demonstrate that the proposed method—through the definition of heterogeneous symbols in mobile interaction networks and the combined use of subgraph extraction and line graph transformation—can be precisely adapted to a wide range of low-engagement link detection tasks, thereby capturing key information across diverse scenarios.

**Table 2.** Average number of nodes and edges in line graphs and subgraphs across detection tasks

| Name | Nodes (Line Graph) | Edges (Line Graph) | Nodes (Subgraph) | Edges (Subgraph) |
|---|---|---|---|---|
| Task 1 | 115.23 | 158.32 | 215.23 | 1235.32 |
| Task 2 | 52.69 | 136.32 | 78.32 | 278.23 |
| Task 3 | 246.32 | 735.62 | 215.64 | 865.21 |
| Task 4 | 539.32 | 1125.36 | 238.26 | 1358.23 |
| Task 5 | 6.12 | 11.58 | 21.54 | 23.51 |
| Task 6 | 728.65 | 1689.62 | 178.23 | 1458.32 |
| Task 7 | 715.23 | 1687.25 | 768.23 | 11256.23 |

**Table 3.** Experimental results of the proposed model on complete, incomplete, and imputed datasets

| | Precision | Recall | F1 |
|---|---|---|---|
| Complete dataset | 0.865 | 0.678 | 0.754 |
| Incomplete dataset with missing edges | 0.889 | 0.632 | 0.742 |
| Imputed dataset | 0.845 | 0.689 | 0.759 |

**Table 4.** Confusion matrix of detection results of the proposed model on complete and incomplete datasets

| | Complete Dataset | | Incomplete Dataset | |
|---|---|---|---|---|
| | Predicted Normal | Predicted Abnormal | Predicted Normal | Predicted Abnormal |
| True normal class | 14526 | 124 | 14526 | 81 |
| True abnormal class | 336 | 736 | 378 | 689 |

Analysis of the data in Tables 3 and 4 demonstrates that the proposed method exhibits strong detection performance and robustness across datasets of varying completeness. In Table 3, the complete dataset yielded a precision of 0.865, a recall of 0.678, and an F1 score of 0.754. On the incomplete dataset, precision increased to 0.889, reflecting the model's sensitivity to critical missing links. After data imputation, the imputed dataset achieved an F1 score of 0.759, indicating that the model retained stable performance following structural restoration. In the confusion matrix in Table 4, on the complete dataset, the model correctly predicted 14,526 true normal samples and 736 true abnormal samples. In the incomplete dataset, 14,526 true normal samples were still correctly identified, and the number of correctly predicted abnormal samples remained relatively high at 689, suggesting that the model maintained strong discriminative capability even under conditions of data loss. Overall, the proposed method demonstrated consistent performance across various data conditions—complete, incomplete, and imputed—accurately distinguishing between normal and abnormal interaction patterns. These results affirm the method's effectiveness and robustness in the context of low-engagement link detection as well as adaptability in complex data scenarios.

## 4 CONCLUSION

To address the challenge of optimizing dynamic strategies for low-engagement students in classroom interaction, a graph link prediction-based evaluation framework for mobile interaction strategies was proposed. A complete technical pipeline was constructed, encompassing data modeling, feature aggregation, and strategy optimization. By defining a heterogeneous symbolic system incorporating students, teachers, and learning resources, mobile interaction networks were transformed into a heterogeneous graph model, thereby overcoming the limitations of traditional approaches that rely heavily on explicit indicators such as speaking frequency. Subgraph extraction and line graph transformation algorithms were developed, focusing on 2–3-hop indirect paths to capture latent structural features such as sparse connectivity and unbalanced unidirectional interactions typically exhibited by low-engagement students. A tree-LSTM aggregation model was introduced to recursively aggregate edge features along directed line graph paths, significantly improving the utilization of multi-order path information. A ranking loss training mechanism was employed to address the issue of positive–negative sample imbalance, thereby strengthening the model's capacity to detect anomalous patterns such as isolated nodes and cross-context interaction discontinuities. Experimental results demonstrated that the proposed method outperformed comparative approaches across seven types of low-engagement detection tasks. In scalability evaluations across datasets of varying sizes, the method exhibited superior robustness in handling both sparse data and complex heterogeneous graph structures, thereby validating the effectiveness of the strategy evaluation loop. The value of the study lies in both methodological innovation and practical applicability. For the first time, tree-LSTM was integrated into educational interaction modeling, yielding a structured analytical framework for latent behavioral detection.

Nevertheless, limitations remain, including strong data dependency, suboptimal computational efficiency, and limited generalizability of strategies. Future research may focus on multimodal deep integration, real-time dynamic learning, ethical and fairness enhancement, and cross-context transfer learning to improve the detection of latent behaviors, adapt to evolving network structures, ensure fairness in intervention strategies, and broaden the applicability of the model. In summary, a systematic solution has been provided for optimizing interactive strategies for low-engagement students, offering meaningful practical guidance for advancing classroom interaction in the era of intelligent education.

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