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PAPER

Construction of a Hybrid Learning Model Based on Mobile Interaction Technology in Vocational Schools and its Mechanism for the Quality Assurance of Teaching

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ABSTRACT

With the continuous advancement of information technology and the widespread adoption of mobile internet and smart devices, profound transformations have been introduced into instructional models within vocational colleges. As an instructional approach that integrates both online and offline resources, the hybrid learning model has gradually emerged as a central direction for educational reform in vocational education. The application of mobile interaction technology has enabled students to engage in real-time and flexible learning interactions through digital platforms, thereby enhancing learning outcomes. However, insufficient attention has been paid to the identification and construction of implicit interaction relationships within hybrid learning environments—particularly on learning platforms underpinned by mobile interaction technology. The effective identification and optimization of implicit learner-to-learner interaction dynamics remain unresolved challenges. Current domestic and international research in hybrid learning and mobile learning platforms has primarily focused on evaluating instructional outcomes and integrating resources, while exploration into implicit interaction patterns has remained limited. Although certain studies have proposed strategies for optimizing hybrid learning models, these approaches often lack data-driven, systematic methodologies and fail to fully uncover implicit learner interactions and underlying needs. To address this study gap, this study seeks to explore methods for discovering and constructing implicit interaction relationships among students within mobile interaction-based learning platforms. Specifically, the study focuses on identifying implicit learner interactions in hybrid learning contexts and proposes a discovery method for such relationships based on an extended mobile interaction graph. The aim is to provide both theoretical grounding and practical guidance for vocational colleges to improve mechanisms that ensure instructional quality and enhance learning effectiveness.

KEYWORDS

hybrid learning, mobile interaction technology, implicit interaction relationship, instructional quality assurance, vocational colleges

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1 INTRODUCTION

With the rapid advancement of information technology—particularly the widespread adoption of mobile internet and smart devices—traditional instructional models have undergone unprecedented transformations [1–4]. Against this backdrop, hybrid learning models, which integrate online and offline educational resources, have been increasingly adopted in vocational colleges as an innovative instructional approach [5, 6]. Mobile interaction technology, characterized by its flexibility and real-time responsiveness, has provided new opportunities for instructional reform in vocational education [7, 8]. Supported by mobile learning platforms, students are now able not only to access learning resources anytime and anywhere [9], but also to engage in knowledge exchange and collaborative learning through various forms of interaction [10], thereby improving overall learning effectiveness. However, several challenges persist in the instructional design and implementation of hybrid learning models, particularly in the effective construction and optimization of implicit interaction relationships among learners.

Despite the growing body of literature on hybrid learning, several gaps remain unaddressed. Existing studies have largely concentrated on the evaluation of instructional outcomes and the integration of learning resources [11–14], while insufficient attention has been directed toward the identification and development of implicit interaction relationships among students—especially those mediated by mobile interaction technologies. Certain studies [15, 16] have relied excessively on traditional instructional data analysis, neglecting the dynamic evolution and individualized characteristics of implicit learning behaviors. This limitation has hindered the full exploration of learners' implicit needs and potential barriers embedded in platform-based interactions. Furthermore, although some research efforts [17, 18] have proposed strategies for optimizing hybrid learning models, the majority of these contributions have remained at the theoretical level and lack systematic, data-driven methodologies applicable to real-world instructional contexts. As a result, practical challenges in hybrid learning environments remain insufficiently addressed.

To address the aforementioned issues, this study was structured around two primary research directions. First, attention was directed toward the discovery and construction of implicit interaction relationships within hybrid learning environments on mobile learning platforms. By conducting in-depth analysis of interaction data among students on these platforms, implicit relationships were revealed, and an effective instructional support system was constructed based on these identified patterns. Second, the study focused on the discovery of user-level implicit mobile interaction relationships based on an extended mobile interaction graph. A novel graph model-based analytical approach was proposed, aimed at comprehensively uncovering implicit learner interactions across multiple dimensions, including interactive behaviors, learning progress, and resource utilization, thereby supporting the development of more precise instructional strategies and personalized guidance schemes for educators. This study is expected not only to enrich the theoretical framework of hybrid learning models but also to offer critical technical support and practical references for quality assurance mechanisms in educational practice.

2 PROBLEM DESCRIPTION: DISCOVERY AND CONSTRUCTION OF IMPLICIT INTERACTION RELATIONSHIPS IN HYBRID LEARNING ON MOBILE LEARNING PLATFORMS

With the accelerated progression of educational digitalization, vocational colleges have increasingly explored the implementation of hybrid learning models. Hybrid learning is not merely a simple combination of traditional in-person instruction and online education; rather, it emphasizes personalization, interactivity, and learner autonomy throughout the instructional process. The integration of mobile interaction technology has introduced new possibilities into hybrid learning environments, offering distinct advantages in enhancing learner engagement and learning effectiveness. Within this context, the present study focuses on the discovery and construction of implicit interaction relationships embedded in hybrid learning environments on mobile learning platforms. Particular emphasis is placed on uncovering and analyzing implicit interactions that may not be overtly manifested but have a significant impact on learning outcomes. These implicit interactions include learner–resource engagement, peer collaboration and discussion, and learner feedback on instructional content. Such interactions often reflect underlying learning needs and directly influence learning performance. Conventional instructional quality assurance mechanisms have primarily relied on periodic assessments and teacher-led classroom interactions while frequently overlooking the importance of implicit learner interactions on digital platforms. A deeper understanding and accurate identification of these implicit relationships may provide a robust theoretical foundation for constructing more adaptive hybrid learning models and offer substantial support for improving instructional quality assurance systems. Figure 1 presents a conceptual diagram illustrating the problem of discovering and constructing implicit interaction relationships in hybrid learning on mobile learning platforms.

Fig. 1. Conceptual framework for discovering and constructing implicit interaction relationships in hybrid learning on mobile learning platforms

Upon completion of the discovery and construction of implicit interaction relationships within hybrid learning on mobile learning platforms, a more personalized and dynamic evolution of the hybrid learning model can be anticipated. Traditional hybrid learning models are typically designed based on static course structures and predefined learning pathways. However, through in-depth analysis of learners' interactive behaviors on mobile platforms, implicit learning needs and interaction patterns can be effectively identified. This form of model enhancement—grounded in implicit interaction relationships—enables the learning platform to operate with greater intelligence, facilitating real-time adjustments to learning content and pathways in response to learners' individual progress, interests, and requirements. For instance, by analyzing participation in discussion groups, resource browsing behaviors, and the frequency of peer interactions, the platform may automatically recommend more targeted instructional content and encourage more effective collaborative learning. Such personalized learning path design not only enhances the overall learning experience but also significantly improves learning efficiency and outcomes, thereby fostering deeper and more self-directed learning among students.

Simultaneously, the instructional quality assurance mechanism must also undergo corresponding optimization in alignment with the evolution of hybrid learning models. Conventional quality assurance approaches—largely dependent on teacher evaluations, classroom observations, and periodic assessments—often fail to capture the implicit behaviors demonstrated by students throughout the learning process. Research on implicit interaction relationships offers a data-driven means to monitor learner behavior on digital platforms in real time, facilitating the early identification of learning difficulties and progress bottlenecks. For example, by analyzing learning trajectories, interaction frequencies, and assignment completion records, learners in need of additional support can be identified, and targeted intervention recommendations can be provided to instructors. This dynamic and personalized quality assurance framework not only increases transparency in the instructional process but also supports educators in designing more effective, student-specific teaching strategies. As a result, a more scientific and adaptive instructional evaluation and assurance mechanism can be achieved.

In the context of hybrid learning on mobile learning platforms, implicit interaction relationships among users were inferred by analyzing user behavior data and interaction information captured on the platform. A formal description of the problem of discovering such implicit user interaction relationships is presented below. An interaction network was defined as $H = (N, R^D, R^Z, X)$, where N denotes the set of users, which consists of two subsets: N_{HI} and N_{NO}, with the former representing the set of hidden users whose interaction relationships are not publicly disclosed and must be inferred and the latter denoting the set of regular users with known and observable interaction relationships. R^D denotes the set of mobile interaction relationships among users, composed of R^D_{HI} and $R^D_{NO}l$, which respectively represent the interaction relationships involving hidden users and regular users. Since interactions may occur between hidden and regular users, R^D_{HI} and R^D_{NO} are not necessarily mutually exclusive. R^Z represents the set of interaction activities among users, where each edge r^Z_{uk} indicates an observed interaction activity between user's u and k. Under this formalism, the interaction relationships R^D_{HI} involving hidden users remain unknown; however, certain interaction activities R^Z_{HI} may be inferred from the observable behavior of regular users. The core research objective, therefore, lies in the development of an appropriate inference function $d(\cdot)$ that utilizes known interaction data to infer the unobserved implicit interaction relationships B among hidden users.

$$d(N, R^D, R^Z, X, \Phi) \rightarrow B \tag{1}$$

In hybrid learning scenarios, the discovery of implicit interaction relationships extends beyond traditional user behavior analysis and must be situated within the context of learning-specific activities, such as resource sharing, discussion participation, and task collaboration. Although the interaction relationships R^D_{HI} involving hidden users (N_{HI}) are not explicitly recorded, potential interaction patterns may be inferred by analyzing the behavioral and learning activity data of regular users. For instance, hidden users may participate indirectly in learning processes through activities such as commenting, engaging in discussions, or sharing resources with regular users, even though such participation is not explicitly represented as observable interactions. By constructing a suitable inference model that incorporates both user attribute information and discourse interaction information, potential learning relationships among hidden users can be effectively revealed. Such an approach not only enhances the representation of the platform's social network structure but also provides critical support for the development of personalized learning pathways, the formation of learning groups, and the optimization of collaborative tasks.

3 DISCOVERY OF IMPLICIT MOBILE INTERACTION RELATIONSHIPS BASED ON AN EXTENDED MOBILE INTERACTION GRAPH

Within mobile learning platforms used in hybrid learning environments, the discovery model for implicit mobile interaction relationships based on an extended mobile interaction graph provides an effective framework for uncovering potential connections among hidden users. The architecture of this model is illustrated in Figure 2.

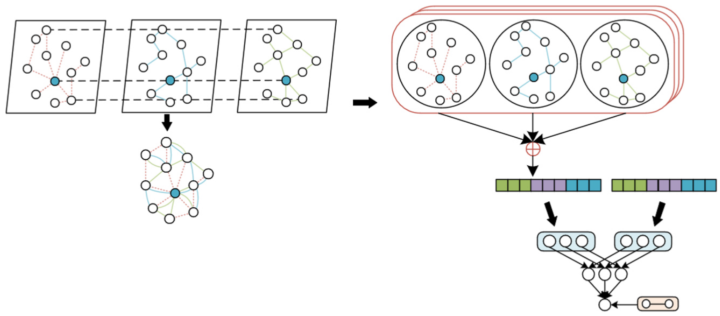


Fig. 2. Framework of the implicit mobile interaction relationship discovery model based on the extended mobile interaction graph

The model integrates three distinct types of information—mobile interaction relationships, user attribute information, and discourse interaction information—to construct an extended mobile interaction graph that incorporates multiple relationship types. In this graph, each node represents an individual user, while edges denote interaction relationships between users. These include explicit mobile interactions, implicit attribute-based connections, and interactions inferred from discourse-based exchanges. By synthesizing these heterogeneous data sources, the model enables the inference of previously undisclosed interaction relationships among hidden users, leveraging the partial interaction data available, thereby supporting personalized learning path recommendations and the formation of collaborative learning groups within hybrid learning environments.

3.1 Extended social graph

Within mobile learning platforms used for hybrid learning, the model for discovering implicit mobile interaction relationships based on an extended mobile interaction graph was enhanced through the integration of user attribute information and discourse interaction information into the existing mobile interaction network structure. This enhancement enriches the interaction network of the learning platform. The original mobile interaction network of the learning platform is denoted as $H_T = (N_T, R_T^D, R_T^Z, X_T)$, where N_T represents the set of users, R_T^D and R_T^Z denote two types of interaction relationships, and X_T is the attribute matrix. These components collectively describe users' interaction behaviors and attribute information. Building upon this foundation, the extended mobile interaction graph incorporates additional user attribute and discourse interaction data to facilitate the discovery of more potential relationships among users. A conceptual illustration of the extended social graph is provided in Figure 3.

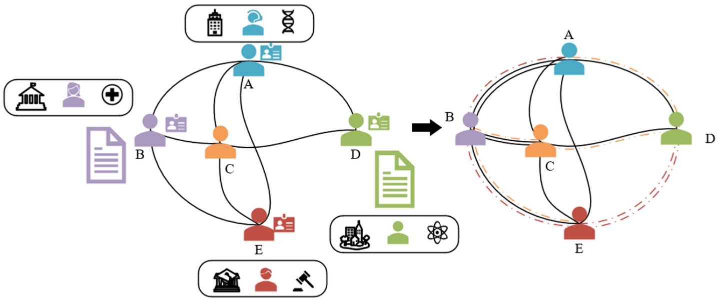


Fig. 3. Diagram of the extended social graph

The attribute matrix X characterizes the distribution of user attributes across the network, while R_T^D and R_T^Z respectively, represent direct mobile interaction relationships and discourse-based interactions among users. Through this structural expansion, the model enables the integration of observable interactions with implicit user relationships, allowing interactions to be inferred not only through direct behavioral engagement but also through shared attributes such as learning backgrounds or common interests. To process this expanded set of information effectively, further treatment of attribute values was conducted. Let the attribute value set be defined as $M = \{m_j\}$, where $l = |L|$ denotes the total number of attribute values. These values are assumed to be mutually exclusive within the same attribute category. For each attribute value m_j, an attribute association relationship was established between users who share the same value. For instance, when users i and n are both associated with the attribute value m_j, an attribute-based link r_{in}^X is constructed between them. By introducing these attribute association relationships, the model extends its capacity to discover not only direct mobile interaction relationships (R_T^D and R_T^Z) but also indirect connections derived from common attribute characteristics.

In hybrid learning environments supported by mobile learning platforms, the extended mobile interaction graph serves as the core structural representation, incorporating three types of edges—R^D, R^Z, and R^X—to characterize different forms of user interaction. The edge type R^D denotes mobile interaction relationships, primarily representing social links such as follower or friend connections. These reflect direct social affiliations and capture basic interpersonal interactions among users. The edge type R^Z represents discourse interaction relationships, which arise through behaviors such as commenting or reposting. These edges capture linguistic exchanges and provide insight into collaborative behaviors occurring during the learning process. The edge type R^X denotes attribute association relationships, constructed through shared user attributes such as common interests or academic domains. These associations facilitate the identification of implicit collaboration patterns among users who exhibit aligned learning preferences. By integrating these three distinct types of relationships into a unified graph structure, the extended mobile interaction graph offers a multidimensional network perspective, which supports a more comprehensive understanding of user behavior and social interaction dynamics. This integration significantly enhances the discovery of implicit interaction relationships, particularly those not directly observable through traditional engagement metrics. To facilitate further analysis, the extended mobile interaction graph is expressed in the form of adjacency matrices. The matrix L represents the overall adjacency matrix of the extended graph, encompassing all types of user interactions. Submatrices L_D, L_Z, and L_X correspond to the adjacency matrices of subgraphs defined exclusively by mobile interaction, discourse interaction, and attribute association relationships, respectively. This matrix-based decomposition allows the model to distinguish among different interaction modalities during analytical processes, thereby enabling tailored handling of their respective influences. For instance, within hybrid learning scenarios, learning groups may be formed through attribute associations, while academic discussions or peer learning may emerge from discourse interactions. By conducting separate analyses of these interaction types, the model is capable of accurately identifying implicit collaborative learning relationships, with particular emphasis on those that remain implicit in the learning environment.

3.2 Convolutional network layer

Given that the extended mobile interaction graph comprises multiple types of edges—namely, mobile interaction relationships, discourse interaction relationships, and attribute association relationships—conventional convolutional neural network (CNN) models cannot be directly applied, as they are typically designed to process homogeneous edge types and are insufficient for capturing the heterogeneity of graph structures. To address this limitation, the convolutional operation was redefined from the perspective of relational structures to ensure that each edge type is appropriately processed. Each node in the graph was encoded as a real-valued one-hot vector, allowing the original node features to be preserved while enabling the network to conduct effective embedding representation learning based on initial node states. In hybrid learning environments, user attributes, discourse content, and social relationships are all critical factors influencing learning behavior. One-hot encoding serves to explicitly represent these features as node-specific input vectors, providing a clear and interpretable foundation for subsequent convolutional operations. Let the hidden state of node u at layer m be denoted as $g(\cdot)$, and the dimension of the m-th layer be represented by $f^{(m)}$. The neighborhood of node u is denoted as $V(u)$. The message-passing activation function is represented by $\delta(\cdot)$, while $L(\cdot)$ refers to a neural network function or a simple linear transformation function. In classical CNNs, $L(g_u, g_p) = Q_{gk}$, leading to the following formulation:

$$g_u^{(m+1)} = \delta\left(\sum\nolimits_{k\in V(u)} L^{(m)}\left(g_u^{(m)}, g_k^{(m)}\right)\right) \tag{2}$$

The initial node (n_u) embedding $g_u^{(0)}$ was defined as the node features:

$$g_u^{(0)} = [a_1, a_2, \ldots, a_v] \tag{3}$$

In this model, the convolutional network layer operates by learning node embeddings through multiple layers of convolution, where node information is propagated via the adjacency matrix. As the extended mobile interaction graph incorporates three distinct types of relationships—mobile interaction (V_D), discourse interaction (V_Z), and attribute association (V_X)—each relationship type imposes different influences on node interactions and information flow. Therefore, in the design of the

CNN, each type of interaction must be separately addressed to capture its respective contribution to the node embedding. The embedding of node n_u at layer m, denoted as $g_u^{(m)}$, was computed based on its own embedding from the previous layer and the embeddings of its neighboring nodes. Assuming that j is D, Z, and X, respectively, where $V_D(\cdot)$, $V_Z(\cdot)$, and $V_X(\cdot)$ represent the social interaction neighbors, discourse interaction neighbors, and attribute association neighbors in the extended social graph, respectively, this leads to:

$$g_u^{(m+1)} = \delta\left(\sum\nolimits_{j\in\{D,Z,X\}}\sum\nolimits_{k\in V_j}\frac{1}{\left|V_j(u)\right|}\Phi^{(m)}g_k^{(m)} + \Phi_p^{(m)}g_k^{(m)}\right) \tag{4}$$

Specifically, each type of relationship in the extended mobile interaction graph is represented by a corresponding adjacency matrix: L_D for mobile interaction relationships, L_Z for discourse interaction relationships, and L_X for attribute association relationships. These adjacency matrices were used to define the relational structure between nodes. For instance, a value of 1 of the u-th row and the k-th column of a given matrix indicates the existence of the corresponding relationship between node n_u and node n_k. The convolutional operation was then performed separately for each type of relationship using its respective adjacency matrix. Each adjacency matrix encodes a distinct path of information propagation and interaction dynamics, thereby enabling the model to integrate heterogeneous information across multiple relational dimensions. In hybrid learning scenarios, users often engage in multifaceted interactions—for example, participating in group activities through social links, engaging in academic discussions via discourse interactions, or forming learning interest groups through shared attributes. Consequently, the convolutional network constructed over the extended mobile interaction graph is capable of uncovering implicit learning relationships from multi-level, multi-dimensional user interaction patterns, thereby enhancing the platform's ability to deliver accurate personalized recommendations and optimize collaborative learning tasks. Let the identity matrix be denoted by U. Then, the adjacency matrix for each layer can be expressed as:

$$L^{(m)} = \sum\nolimits_{j\in\{D,Z,X\}}(\Phi^{(m)}L_j) + 1 \tag{5}$$

The final node embedding representation is given by:

$$G^{(m+1)} = \delta(L^{(m)}G^{(m)}\Phi^{(m)}) \tag{6}$$

3.3 Prediction scoring layer

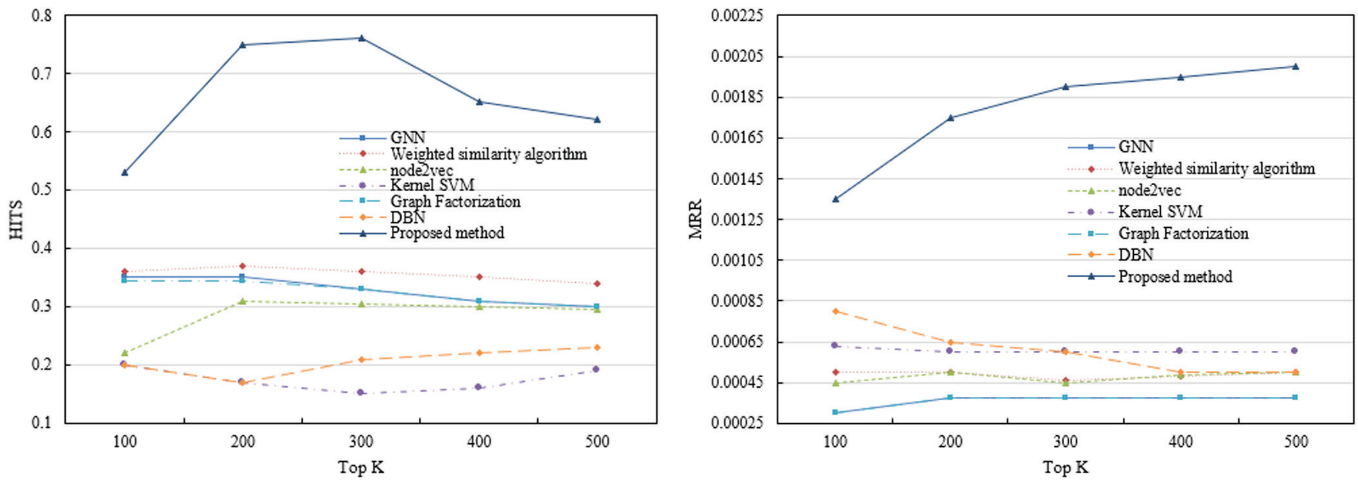
Within the model framework, the prediction scoring layer is designed to evaluate the likelihood of potential mobile interaction relationships between user node pairs by computing their final embedding representations. Following training through multiple layers of the CNN, a set of node embeddings was generated, denoted as $C = \{c_0, c_1, \ldots, c_{|N|}\}$, where each vector encodes the interaction-related information of the node with other nodes in the graph. To accurately predict whether a mobile interaction relationship exists between a given node pair (n_u, n_k), the model calculates a score based on their respective embeddings. This score represents the degree of implicit association between the two nodes. In the context of a hybrid learning platform, this scoring mechanism enables the prediction of user behaviors, supporting the identification of potential learning collaborations or interaction opportunities among students. Let the probability that a mobile interaction link exists between nodes n_u and n_k be denoted as o_{uk}. To model this, a scoring function was designed to jointly consider the influence of the three types of relationships—mobile interactions, discourse interactions, and attribute associations—as follows:

$$o_{uk} = \sum\nolimits_{j \in \{D,Z,X\}} c_u^S F_j c_k \tag{7}$$

To improve prediction accuracy during training, a semi-supervised graph autoencoder approach was employed. In this process, the model is trained not only on real mobile interaction data but also on T negative samples, which are randomly selected node pairs that do not possess direct mobile interaction relationships. These negative samples serve as contrastive examples, enabling the model to learn to distinguish between observed and unobserved interactions and thereby enhancing its ability to infer implicit connections. During the decoding phase, the model integrates the influence of all three relationship types when evaluating node pairs. A cross-entropy loss function was adopted as the objective function to minimize prediction error. This ensures that the model accurately infers implicit mobile interaction relationships between users. Let $\varphi(\cdot)$ denote the logistic function, and the cross information entropy was used as the objective function of the research question as follows:

$$M = -\frac{1}{(1+T)|R|}\sum\nolimits_{(u,k)\in F} b\log\phi(o_{uk}) + (1-b)\log(1-\phi(o_{uk})) \tag{8}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS



a) HITS

b) MRR

Fig. 4. Results of implicit interaction relationship discovery in hybrid learning based on the learning path dataset

Experimental results derived from the learning path dataset, as illustrated in Figure 4, demonstrated that the proposed method significantly outperformed baseline models across both evaluation metrics, i.e., hyperlink-induced topic search (HITS) and mean reciprocal rank (MRR). In the HITS evaluation, the proposed approach consistently yielded superior performance across all Top-K values. It substantially exceeded the results of competing algorithms, such as graph neural network (GNN), which reached a maximum HITS score of only 0.35, and the weighted similarity algorithm, which achieved a peak score of 0.37. In the MRR evaluation, the proposed model similarly exhibited robust performance. Specifically, at Top-K = 500, the method achieved an MRR score of 0.002, considerably outperforming GNN (0.000375) and kernel support vector machine (SVM) (0.0006). These findings indicate that the proposed method maintains strong scalability and predictive capability on large-scale datasets and effectively enhances link prediction accuracy. Its performance highlights considerable potential in uncovering implicit interaction relationships within hybrid learning environments.

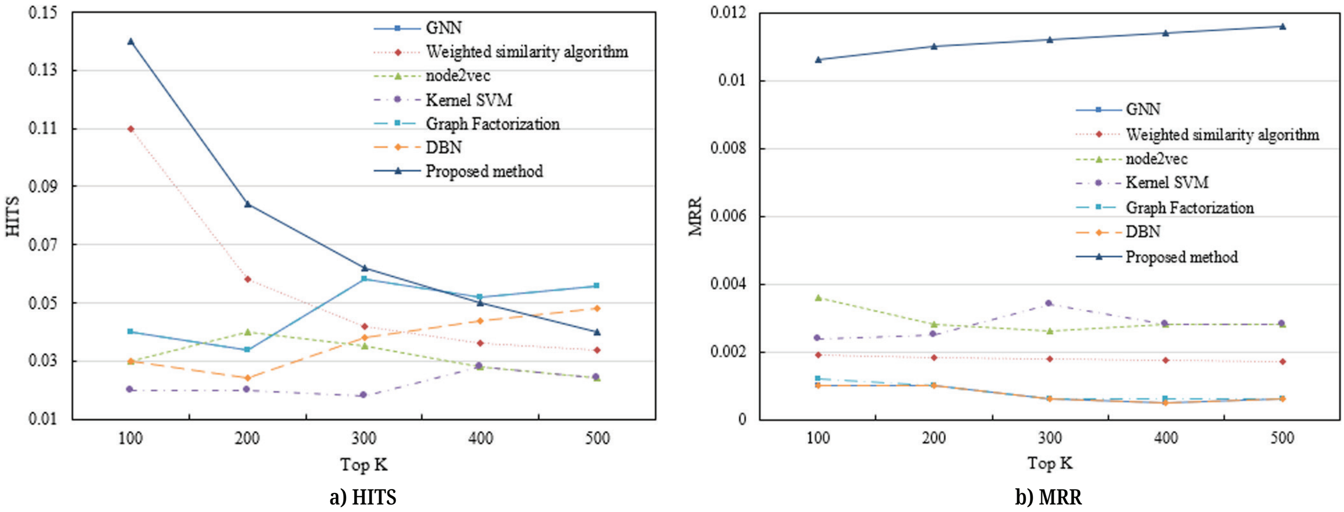
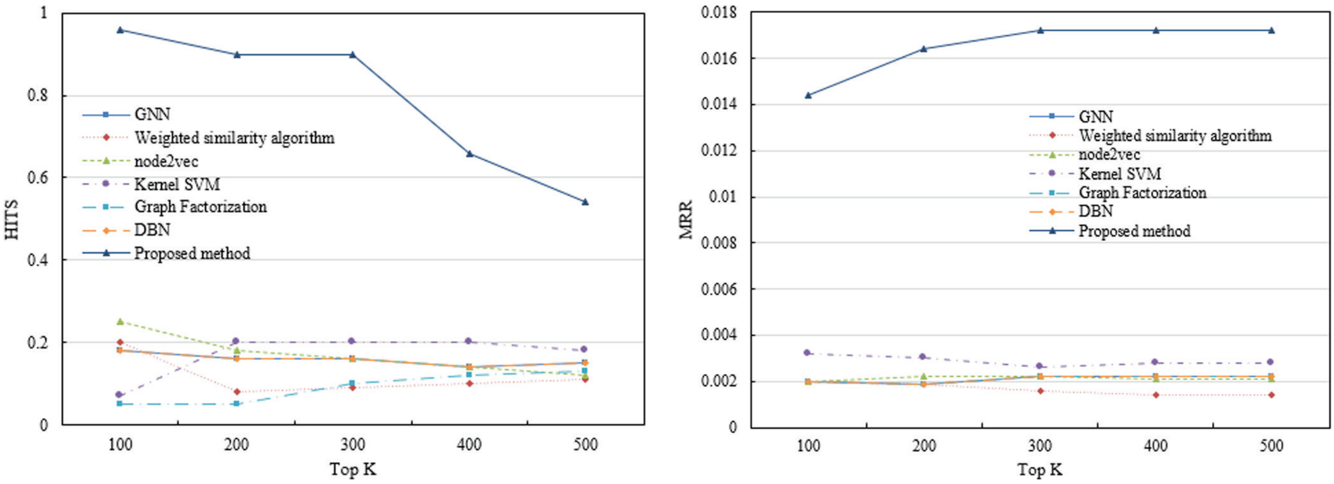


Fig. 5. Results of implicit interaction relationship discovery in hybrid learning based on the online behavior dataset

According to the experimental results based on the online behavior dataset, as shown in Figure 5, the proposed method demonstrated superior performance across both the HITS and MRR evaluation metrics. For the HITS metric, the proposed model achieved a score of 0.14 at Top-K = 100, significantly surpassing the performance of other methods such as GNN (maximum of 0.056) and the weighted similarity algorithm (maximum of 0.11). These results indicate that the proposed method offers enhanced accuracy in predicting potential interaction links. Even at Top-K = 200, where a general decline in performance was observed across all models, the HITS value of the proposed approach remained the highest at 0.084, continuing to outperform alternative methods. With respect to the MRR metric, the proposed model achieved a value of 0.0106 at Top-K = 100, which far exceeded the performance of other baselines, including the weighted similarity algorithm (maximum of 0.0019) and node2vec (maximum of 0.0036). Moreover, the MRR score of the proposed method continued to increase steadily with larger Top-K values, further validating its effectiveness in accurately predicting potential interaction relationships, particularly in large-scale datasets.

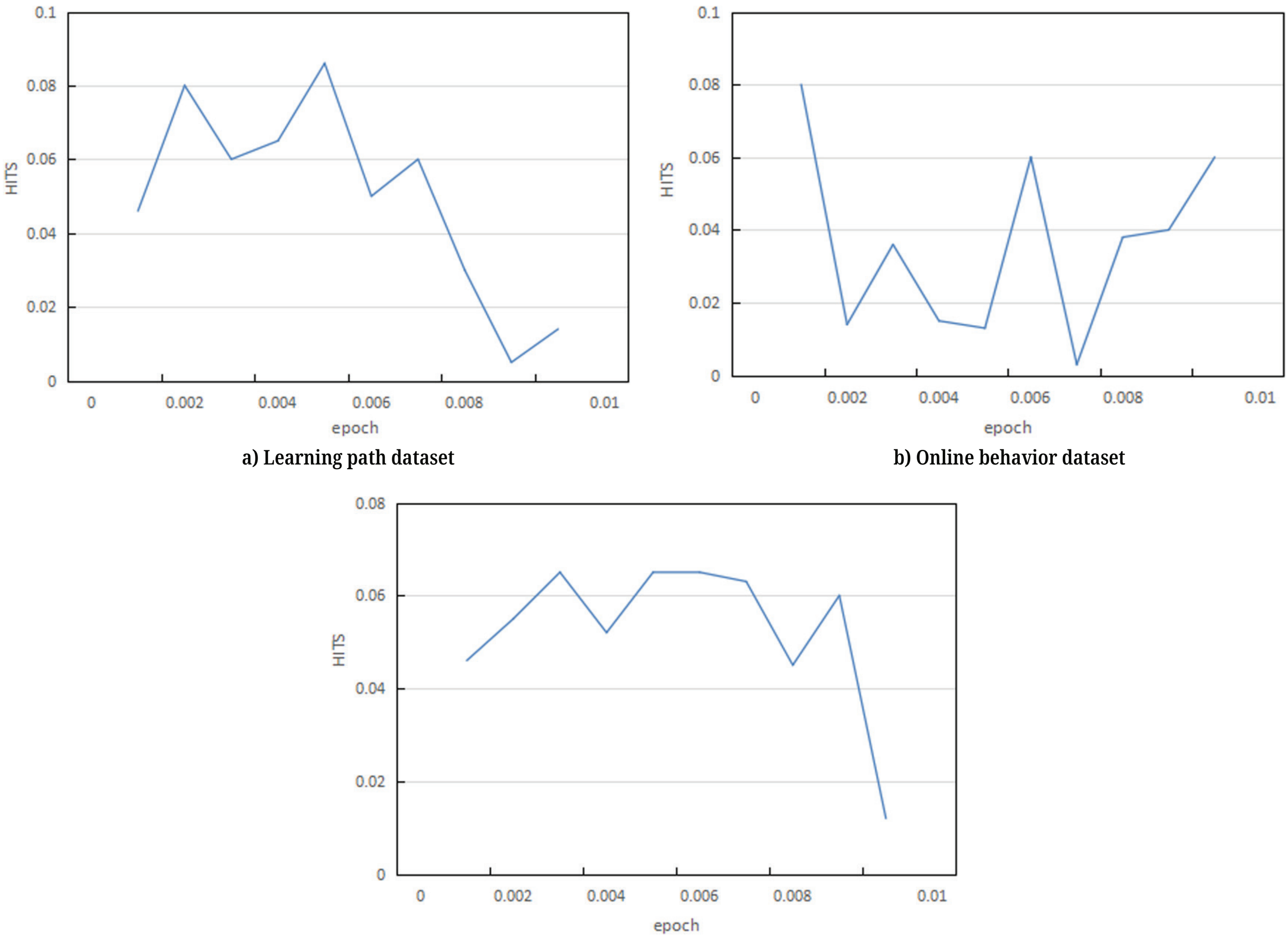
Based on the experimental results obtained from the learning activity dataset, as illustrated in Figure 6, the proposed method demonstrated significant advantages across both evaluation metrics—HITS and MRR. In terms of HITS, the proposed model achieved a score of 0.96 at Top-K = 100, substantially outperforming all baseline algorithms, including GNN (maximum of 0.18), the weighted similarity algorithm (maximum of 0.20), and node2vec (maximum of 0.25). Although a slight performance decline was observed as Top-K increased, the model maintained a high HITS score of 0.90 at Top-K = 200, reflecting both its efficiency and predictive accuracy. Regarding the MRR metric, the proposed approach likewise delivered superior performance. At Top-K = 100, the model achieved a score of 0.0144. As Top-K increased, the MRR score continued to rise steadily, reaching a stable value of 0.0172 at Top-K = 500. These results indicate that the proposed method significantly outperformed other approaches in predicting implicit interaction relationships among learners, particularly when compared with GNN (maximum MRR of 0.0022) and the weighted similarity algorithm (maximum MRR of 0.002).



a) HITS

b) MRR

Fig. 6. Results of implicit interaction relationship discovery in hybrid learning based on the learning activity dataset



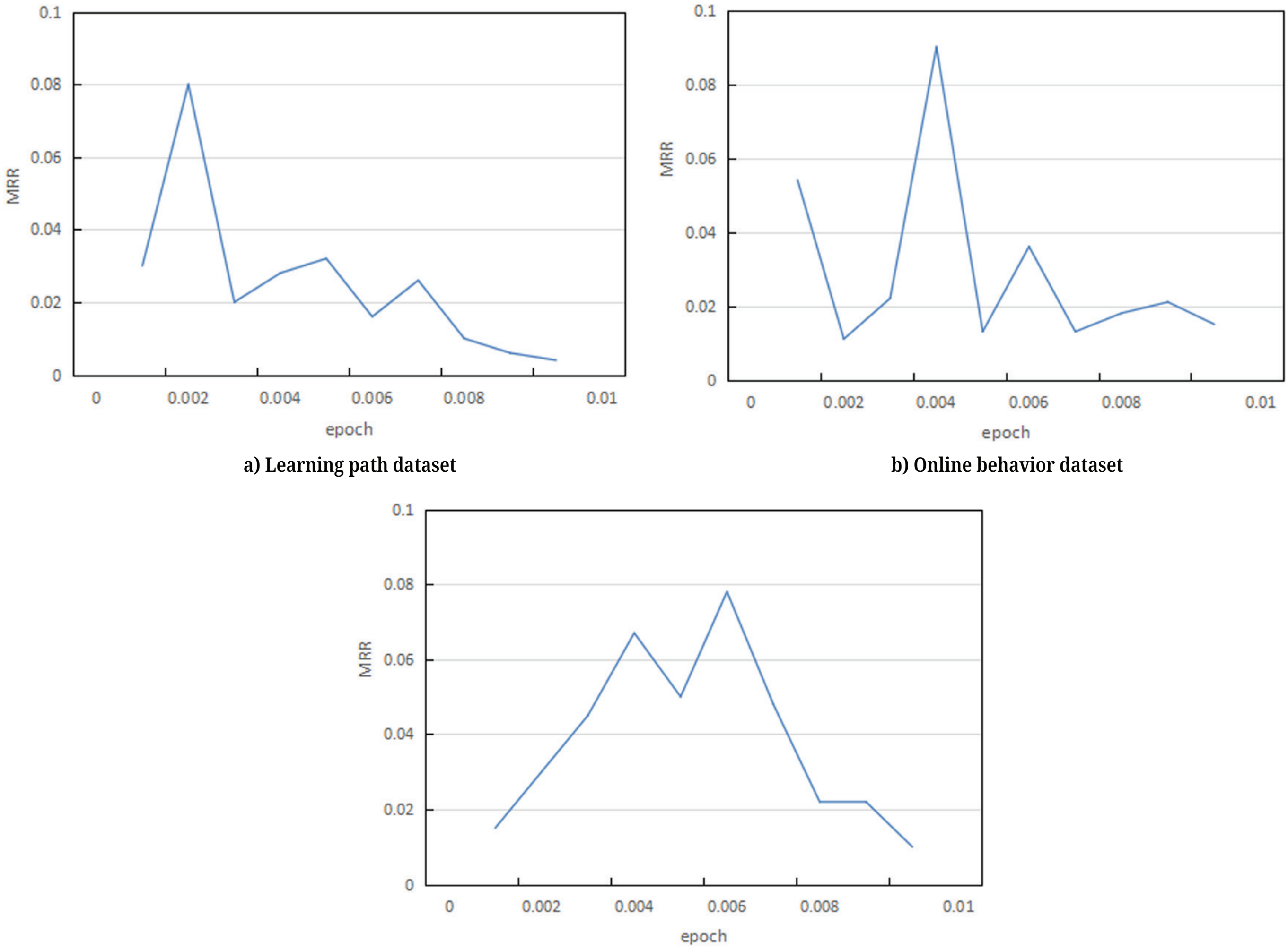
a) Learning path dataset

b) Online behavior dataset

c) Learning activity dataset

Fig. 7. Epoch-wise performance analysis (HITS metric)

As shown in Figure 7, the HITS performance of the proposed method exhibits notable differences across the three datasets when analyzed across varying epochs. For the learning path dataset, an initial HITS value of 0.046 was observed at epoch 0.001. As the number of epochs increased, performance improved steadily, reaching a peak of 0.086 at epoch 0.008, showing a certain upward trend. However, beyond this point, a performance decline was recorded, with the HITS score decreasing to 0.05. For the online behavior dataset, the HITS score was 0.08 at epoch 0.001, followed by a sharp decline to 0.014 at epoch 0.002. A partial recovery was subsequently observed, with HITS rising to 0.06 at later epochs, suggesting unstable convergence behavior in this dataset. In contrast, as for the learning activity dataset, the initial HITS value at epoch 0.001 was 0.046, followed by a consistent increase as training progressed. By epoch 0.008, the HITS score stabilized around 0.065. Overall, HITS performance across all three datasets demonstrated some degree of fluctuation. While improvements were observed at specific epochs, temporary declines in performance also occurred.



a) Learning path dataset

b) Online behavior dataset

c) Learning activity dataset

Fig. 8. Epoch-wise performance analysis (MRR metric)

According to the MRR data presented in Figure 8, the proposed method exhibited noticeable fluctuations in performance across the three datasets. For the learning path dataset, an MRR of 0.03 was observed at epoch 0.001, which increased to 0.08

at epoch 0.002. However, the performance declined thereafter, dropping to 0.004 by epoch 0.01, indicating volatility in performance. In the online behavior dataset, the MRR initially showed a relatively high value of 0.054 at epoch 0.001. This was followed by fluctuations in the subsequent epochs, with a notable peak at epoch 0.006, where the MRR reached 0.09, showing short-term improvement. However, the MRR dropped again in the following epochs (0.008 and 0.01), reaching lower values of 0.036 and 0.015, respectively. Finally, for the learning activity dataset, the MRR value was 0.015 at epoch 0. As the number of epochs increased, the MRR gradually increased, reaching 0.078 at epoch 0.008, suggesting that the model provided more accurate predictions of student interaction relationships as learning progressed. However, by epoch 0.01, the MRR decreased again to 0.01.

Despite the observed fluctuations in performance, the proposed method demonstrated a more stable and gradually improving trend in the learning activity dataset, suggesting that the model is capable of continuously improving its predictive accuracy over the course of long-term learning process data. Through this relationship-based graph model analysis, educators can gain a better understanding of the implicit interaction relationships among students. Based on these in-depth insights, personalized teaching strategies can be developed, and hybrid learning models can be optimized to further enhance the quality of instruction.

5 CONCLUSION

This study is devoted to the discovery and construction of implicit interaction relationships in hybrid learning environments based on mobile learning platforms. By performing in-depth analysis of interaction data among students, implicit interaction patterns were revealed and used to construct an effective instructional support framework, aiming to enable educators to more accurately interpret and predict student behavior, thereby facilitating the design of personalized teaching strategies and intervention plans. The core of the study centers on the use of the graph-based model to analyze multiple dimensions of learner behavior—including interaction patterns, learning progress, and resource utilization—to comprehensively uncover implicit peer-to-peer relationships. This approach demonstrates its effectiveness in revealing implicit learning dynamics and supports the optimization of hybrid learning models to enhance both instructional effectiveness and student performance. The results confirm the potential of the graph-based analytical method in the discovery and construction of implicit interaction relationships. Particularly in the domains of instructional support and personalized guidance, the proposed method shows marked advantages. Experimental evaluations validate the method's superior performance on multiple datasets, especially in terms of the HITS and MRR metrics, where it outperforms traditional techniques in capturing the accuracy and precision of implicit interaction link predictions. As a result, more precise instructional strategies can be formulated, contributing to the overall improvement of hybrid learning models and learning outcomes.

Nonetheless, this study has certain limitations. First, some degree of performance fluctuation was observed across different datasets, especially at specific training epochs, which may be attributable to data variability and noise. Second, despite the demonstrated effectiveness of the graph-based analysis method, its computational complexity remains relatively high, potentially restricting scalability in large-scale educational platforms. Future research could be extended in several directions. One direction involves incorporating multimodal data sources—such as voice, video, and affective signals—to further improve the accuracy and robustness of the model. Another direction involves algorithmic refinement to reduce computational overhead and enable large-scale application in educational environments. Additionally, integrating real-time learning data into the model may facilitate the dynamic adjustment and prediction of student behavior, further enhancing the responsiveness and personalization of educational support systems.

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