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PAPER

The Role of Mobile Technology in Enhancing Classroom Interaction for Accounting Instructors in Higher Vocational Education

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ABSTRACT

The rapid advancement of mobile technology has introduced new opportunities to enhance classroom interaction, particularly in higher vocational accounting education, where theory and practices are closely integrated. Traditional interaction modes often limit student engagement and participation due to constraints of time, space, and format. This study addresses the gap in research on the interactive behaviors of accounting instructors under mobile network environments, focusing on two key aspects: (1) analyzing the effectiveness and influencing factors of mobile technology in facilitating instructor-student interactions in various teaching contexts, and (2) developing a predictive model using data mining techniques to forecast instructor interaction behaviors. By providing data-driven insights and a theoretical foundation, this study aims to optimize classroom interaction, improve teaching quality, and contribute to educational reform in accounting education.

KEYWORDS

mobile technology, higher vocational education, accounting education, classroom interaction, instructor behavior analysis, behavior prediction

1 INTRODUCTION

With the rapid development of information technology, the application of mobile technology in the field of education has gradually gained widespread attention [1–4]. As an important platform for cultivating technical and skilled talents, higher vocational colleges face the dual challenge of improving teaching quality and classroom interaction efficiency [5, 6]. In the teaching of accounting, the interaction between teachers and students is an important link in enhancing teaching effectiveness. However, traditional classroom interaction forms are limited by space and time, often failing to fully stimulate students' interest and enthusiasm for learning [7, 8]. In recent years, the introduction of mobile technology has brought new opportunities

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to education. Through mobile devices such as smartphones and tablets, teachers and students can communicate information anytime and anywhere, making classroom interaction more flexible and diverse. Therefore, how to use mobile technology to improve the classroom interaction effectiveness of accounting teachers in higher vocational colleges has become an important topic in current educational study.

This study aims to explore the application effect of mobile technology in accounting classroom interaction in higher education, analyzing its role in improving teaching quality. By studying the role of mobile technology in classroom interaction, not only can theoretical support be provided for accounting education in higher vocational colleges, but it can also serve as a reference for teaching reforms in other disciplines [9–12]. As society's demands for the quality of higher vocational college education continue to rise, the interaction between teachers and students is not only about knowledge transmission but also involves the collision of ideas and the enhancement of abilities. Therefore, the application of mobile technology in classroom interaction is of far-reaching significance. It helps optimize classroom teaching modes, promotes innovation in teaching methods, enhances students' learning enthusiasm and participation, and thus contributes to the overall improvement of educational quality.

Currently, study on mobile technology and classroom interaction at home and abroad mainly focuses on student interaction, teacher role transformation, and other aspects. However, there is still a lack of specific analysis and prediction of the classroom interaction behaviors of accounting teachers in higher vocational colleges [13–16]. Most studies focus more on the theoretical framework and model construction of classroom interaction, with less attention to specific behavioral analysis and data support, especially regarding the specific performance and influencing factors of teacher interaction behaviors in mobile technology application scenarios. Systematic research results on this have not yet been formed [17–19]. Therefore, existing study methods generally have limitations, such as insufficient exploration of interactive behaviors and limited application of data analysis techniques.

The study in this paper aims to fill this gap and mainly includes two parts. The first part is the analysis of classroom interaction behaviors of accounting teachers in higher vocational colleges under mobile network environments, exploring their specific performance and influencing factors in different teaching contexts. The second part is to predict teacher classroom interaction behaviors through data mining and prediction models, thereby providing references for educational decision-making. Through these two parts of the research, this paper hopes to provide a more scientific and systematic analysis and prediction of classroom interaction in accounting education in higher vocational colleges, improve the effectiveness of teaching methods, and promote the improvement of student learning outcomes.

2 PROBLEM DESCRIPTION OF CLASSROOM INTERACTION BEHAVIOR ANALYSIS OF ACCOUNTING TEACHERS IN MOBILE NETWORK-BASED HIGHER EDUCATION INSTITUTIONS

In the accounting classroom teaching of higher vocational colleges, the interaction between teachers and students is an important factor influencing teaching effectiveness. Traditional classroom interaction methods are often limited to face-to-face communication, and the frequency and quality of interaction are difficult to continuously and effectively improve. However, with the introduction of mobile technology, teachers and students can interact through smart devices, overcoming the limitations of time and space. This form of interaction is not only more flexible but also effectively increases the frequency and depth of communication between teachers and students, thereby enhancing the classroom atmosphere and improving learning enthusiasm. Therefore, predicting the interaction behavior of accounting teachers in the classroom not only helps to gain insights into the interaction patterns between teachers and students but also reveals which interactive behaviors play a greater role in enhancing classroom teaching effectiveness. By predicting these behaviors, teachers can adjust their interaction strategies based on the results, thereby more accurately applying mobile technology in actual teaching to optimize classroom interaction and improve teaching effectiveness.

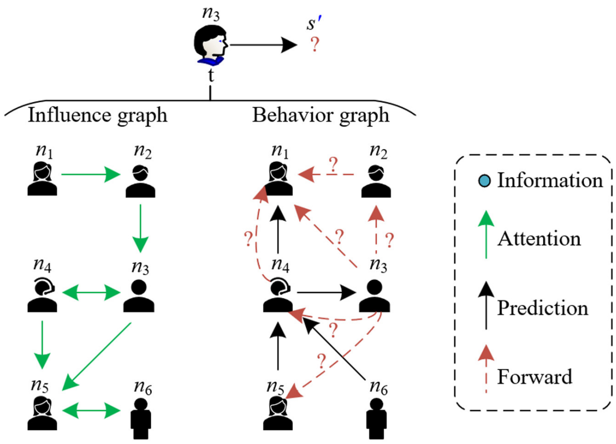

Fig. 1. Communication process of teacher-student classroom interaction behavior

The core goal of this paper's analysis of the classroom teacher-student interaction behavior in mobile network-based higher education institutions is to explore the interaction patterns between accounting teachers and students in the classroom by constructing and analyzing the communication process of classroom teacher-student interaction behaviors and predicting future possible interaction behaviors. Figure 1 presents a schematic diagram of the communication process of teacher-student classroom interaction behavior. The research model defines a teacher-student node set $N = \{n_1, n_2, n_3, \ldots, n_V\}$ and a classroom teacher-student interaction behavior set $L = \{l_1, l_2, l_3, \ldots, l_J\}$, where V represents the number of teachers and students, and J represents the number of classroom teacher-student interaction behaviors. In this framework, each classroom teacher-student interaction behavior l_j will be transmitted and communicated between the node set N. The communication process of each behavior is a time series, recording the moment each behavior occurs and the activation state of the related nodes. Through such modeling, this paper views each classroom interaction behavior as a "file," during which the teacher and student nodes are continuously activated, forming an interactive communication process. In the prediction of classroom interaction behaviors, this paper further combines the characteristics of time series and proposes a prediction method based on a time embedding strategy. Specifically, assuming that a certain node can only be activated once in the time series, the communication process of each interaction behavior can be recorded through time steps, as shown in Figure 1, which demonstrates the communication process of different behaviors and the dynamic changes of the interaction relationship and behavior graphs between teachers and students.

In the prediction of classroom teacher-student interaction behavior communication, the goal of prediction is to forecast the interaction behavior communication at the future time $s + 1$, based on the known interaction behavior state at time s, combined with the influence graph and behavior graph between the teacher and student. In this prediction model, the relationship between teacher nodes and interaction behaviors is not only influenced by direct behaviors but is also closely related to the "influence" of each teacher node. The influence graph provides the relationship weights between each node and other nodes to measure a teacher's communication ability and influence range in classroom interaction, while the behavior graph characterizes the communication path of classroom interaction behaviors, showing how a certain interaction behavior is transmitted between teachers and students.

3 CLASSROOM INTERACTION BEHAVIOR PREDICTION OF ACCOUNTING TEACHERS IN MOBILE NETWORK-BASED HIGHER EDUCATION INSTITUTIONS

This paper uses a deep learning-based framework to predict teacher-student interaction behaviors in accounting classrooms in higher education institutions, aiming to enhance classroom interaction effectiveness through an efficient model. This framework integrates the classroom teacher-student interaction behavior graph, influence graph, and time series information, fully utilizing graph convolutional networks and time embedding mechanisms to capture complex teacher-student interaction patterns. First, the framework learns the structure of the teacher-student interaction behavior graph and influence graph through multi-layer graph convolutional networks, extracting implicit information about interaction and influence propagation between teachers. Further, to better capture the temporal characteristics of classroom interaction, this paper embeds the time series into heterogeneous graphs, incorporating time factors into the interaction behavior prediction process. Teacher and student interaction behaviors in the classroom are influenced not only by the current moment but also by the accumulation and evolution of historical behaviors. To further address the context dependence problem, the framework also adopts a multi-head attention network mechanism. This mechanism allows parallel processing of different contextual information across multiple attention heads while focusing on multiple important feature dimensions, thereby effectively improving the model's ability to recognize complex interaction patterns.

3.1 Interaction behavior representation learning

In this study, the structure of teacher-student interaction behaviors in the classroom is constructed based on a heterogeneous network framework. By combining the influence and behavior relationships of accounting teachers, more accurate classroom interaction behavior predictions are achieved. The construction of the heterogeneous network is based on the influence graph and behavior graph between accounting teachers and students, learning teacher representations by focusing on two different types of relationships: attention relations and recommendation relations. The attention relationship in the influence graph is an unweighted directed graph, representing a teacher's attention and influence on other students. This attention relationship reflects the mutual influence between teachers, capturing which teacher-student pairs have strong interaction relationships and which teachers' behaviors may impact other students. Therefore, by learning the adjacency matrix of the attention relationship D_X, we can understand the position of each teacher in the classroom interaction and their influence in the network. The behavior graph captures the interaction patterns between teachers and students through recommendation relationships. The teaching content recommendation relationship in the behavior graph is a directed and weighted graph, representing the specific teaching content recommended by a teacher to students at a certain moment. This weighted graph records the frequency and intensity of recommendation behaviors, i.e., the teacher's preferences for certain classroom interaction behaviors and historical recommendations of teaching content. Therefore, by learning the adjacency matrix D_s^S of the recommendation relationship, we can obtain each teacher's role in the teaching content recommendation behavior interaction and their activity level in classroom interaction.

This paper uses multi-layer graph convolutional networks to perform structural learning on spatial factors such as influence and communication behavior in classroom interaction behaviors, thereby accurately capturing the complex relationships between teachers and students. The basic principle is shown in Figure 2.

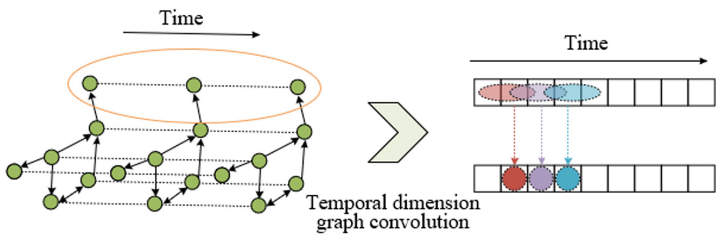

Fig. 2. Structural learning principle

Specifically, the learning of influence and communication behavior in the spatial dimension mainly focuses on modeling the mobile interaction network structure and interaction patterns between teachers and students. The influence relationship between teachers and students has a subtle characteristic, which is usually formed gradually through long-term interaction and communication. This relationship directly affects the communication effectiveness of teacher-student interaction behaviors in the classroom. Through graph convolutional networks, this paper can effectively extract the structural features of teacher-student interaction behaviors from the attention relationships in the influence graph and the recommendation relationships in the behavior graph, learning the degree of mobile interaction between different teachers and students in the classroom. By analyzing the interaction sequences between teachers and students, the model can learn their mobile interaction relationships and interaction habits, thereby predicting their future behavioral tendencies. Specifically, assume that the learnable parameters are represented by $Q_X^{(v)}$ and $Q_S^{(v)}$, the time interval of the heterogeneous network is represented by s_u, the embedding dimension of teacher-student nodes is represented by f, the number of GCN layers is represented by v, the teacher attention relationship at the v-th layer is represented by $A_X^{(v)}$ the teacher recommendation relationship at the v-th layer is represented by $A_S^{(v)}$, and the normally distributed randomly initialized embedding is represented by $A^{(0)}$. The $\delta(\cdot)$ function adopts the ReLU activation function. The learning mechanism of structural learning can be represented as:

$$\begin{gathered} A_X^{(v+1)} = \delta(D_X A^{(v)} Q_X^{(v)}) \\ A_S^{(v+1)} = \delta\left(D_{s_u}^S (A^{(v)} + s_u) Q_S^{(v)}\right) \end{gathered} \tag{1}$$

3.2 Interaction behavior representation fusion mechanism

The influence graph and behavior graph provide the attention relationship and recommendation relationship between teachers and students, and their roles complement each other in classroom interactions. To better integrate these two relationships in deep learning, this paper introduces the attention mechanism. Figure 3 shows the fusion mechanism framework of the influence graph and behavior graph. In this mechanism, for each node n_u, the attention relationship weight in the influence graph and the recommendation relationship weight in the behavior graphs are first calculated. Through the attention network, the importance of these two relationships is dynamically learned. Furthermore, to improve the accuracy of the fusion, this paper uses the Hadamard product operation to combine the obtained weight matrix with the relationship representations of accounting teachers. The Hadamard product is an element-wise multiplication operation that can accurately match the relationship weights learned by the attention network with the teacher's original features, thereby generating more representative interaction behavior representations. Specifically, let the high-dimensional node feature mapping be represented by $x(\cdot)$, the feature matrices of the attention relationship and recommendation relationship be represented by g_u and g_k, the learnable parameters be represented by Q, the attention coefficient between nodes n_u and n_k be represented by β_{uk}, the leakage-corrected linear unit be represented by $LeakReLU(\cdot)$, and the Hadamard product be represented by $\otimes$. The behavior representation at a certain time interval s is represented by $A^{(v+1)}$, and the calculation formula is:

$$\begin{gathered} r_{uk} = x\left(\left[Qg_u \| Qg_k\right]\right), k \in N \\ \beta_{uk} = \text{softmax}(r_{uk}) \\ A^{(v+1)} = \beta_{uX} \otimes A_X^{(v+1)} + \beta_{uS} \otimes A_S^{(v+1)} \end{gathered} \tag{2}$$

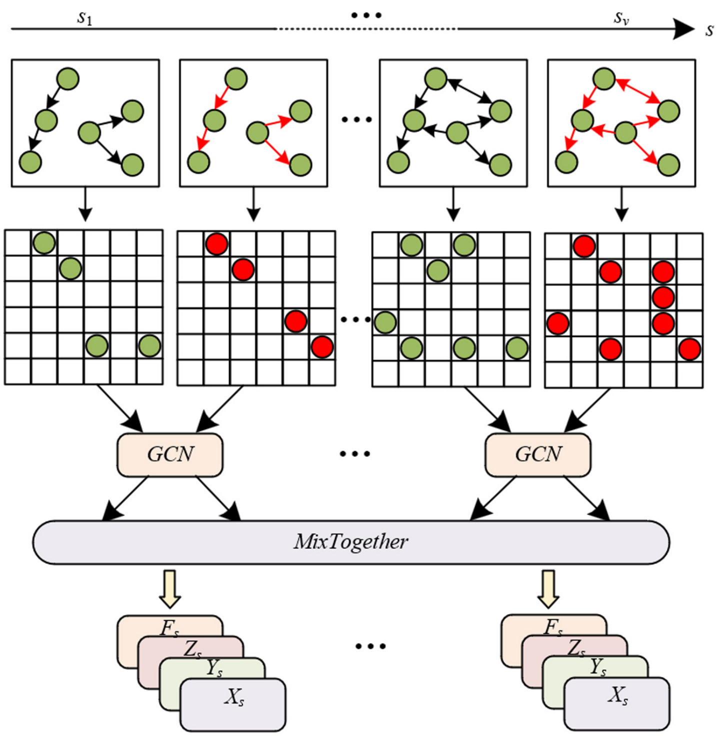

Fig. 3. Fusion mechanism framework of influence graph and behavior graph

3.3 Interaction behavior prediction

To improve the accuracy of classroom interaction behavior prediction for accounting teachers in higher education institutions, this paper adopts two different time embedding strategies. The first strategy is an approximation strategy, and its core idea is to predict classroom interaction behaviors based on temporal continuity. Although the teacher-student interaction behavior graph at each moment is different, the teacher's focus does not change drastically and has strong continuity. Therefore, when predicting classroom interaction behavior at a certain moment, the model uses the classroom interaction behavior graph from the previous moment as the accounting teacher's representation for the current moment's prediction. This strategy assumes that the teacher's behavior changes continuously over time rather than instantaneously jumping, which can effectively capture the gradual trend of teacher behavior in the classroom interactions. Especially in dynamic classroom environments, teacher-student interaction behaviors are influenced by long-term accumulation.

However, the approximation strategy, while capturing some temporal changes, does not fully utilize the information of the entire time series. To address this challenge, this paper further proposes a time embedding strategy based on the attention mechanism. This strategy introduces all historical behavior information from the time series to infer the current accounting teacher's representation, rather than relying on the teacher's representation at a single moment. Specifically, through multi-layer graph convolutional networks, the model can obtain the interaction behavior representation at each time point $[A_{s1}^{v}, A_{s2}^{v}, A_{s3}^{v}, \ldots, A_{sm}^{v}]$, and use the attention mechanism to weight and aggregate these representations across different time points, thus calculating the final accounting teacher representation at time s. Through the attention mechanism, the model can dynamically adjust the weight of the representations at each time point based on their influence in time series, making more relevant historical behaviors have a greater impact on the current moment's prediction. Specifically, let j be a masking matrix. When $s' \geq s_k$, i.e., $j = -\infty$, the attention is turned off when the time exceeds the range. Then:

$$\begin{gathered} s' = \text{mixTogether}(s_7) \\ \beta = \text{softmax}(N_s s' + j) \\ n' = \sum_{u=1}^{S} \beta_u N_{s_u} \end{gathered} \tag{3}$$

The mixTogether function in the above formula represents the time interval embedding.

After obtaining the accounting teacher node representations, these node representations are further constructed into a communication sequence $N = \{n'_1, n'_2, \ldots, n'_V\}$, where each node n'_i represents the features of the accounting teacher at a certain moment or time period. To enhance the expressive power of these node representations, the model uses a linear mapping with shared parameters to increase the dimensionality of the node representations. Through this dimensionality increase operation, the model can map the original low-dimensional features into a higher-dimensional space, making each node representation richer and more accurate. Then, the Mask an Attention mechanism is applied to further process these node representations. The core idea of the Mask Attention operation is to perform attention computation only on nodes that meet specific conditions, rather than performing the computation on all nodes. In this way, the model can focus on nodes that have a significant impact on classroom interaction behavior at specific moments or under specific conditions, avoiding the interference of irrelevant nodes and improving prediction accuracy and efficiency. Specifically, let Z be a mask matrix, and when $u > k$, i.e., $Z = -\infty$, the attention is turned off when the time exceeds the range. Suppose the learnable parameters are represented by Q_u^W, Q_u^J, Q_u^N, Q^P, and the number of heads in multi-head attention is represented by V. The formula for classroom teacher-student interaction behavior prediction is then:

$$
\begin{gathered}
F_u = \text{softmax}\left(\frac{N'Q_u^W(N'Q_u^J)^S}{\sqrt{f_e}} + Z\right)N'Q_u^N \\
L = \left[f_1; f_2; \ldots; f_V\right]Q^P
\end{gathered}
\tag{4}
$$

Finally, the model calculates the probability of classroom interaction behavior exchange through a two-layer fully connected neural network. Specifically, after performing Mask Attention, the resulting node representations are processed through fully connected layers to obtain the behavior prediction for each accounting teacher at a specific time. Suppose the probability that the teacher recommends learning content to the student is represented by o, the learnable parameters are represented by η_1, η_2, and the activation function is represented by $\delta(\cdot)$. The formula for calculating the probability of classroom teacher-student interaction behavior exchange is:

$$
o = Q'\delta(Q''L^S + \eta_1) + \eta_2 \tag{5}
$$

This paper uses the cross-entropy loss function as the objective function, aiming to minimize the difference between the predicted results and the true labels. The cross-entropy loss function is commonly used for the classification problems and can effectively measure the distance between the predicted probabilities and actual labels:

$$
\Psi(\phi) = -\sum_{u=2}^{M}\sum_{j=1}^{|I|} o_{uj}\log(\hat{o}_{uj}) \tag{6}
$$

By training the neural network, the model can automatically learn the key factors in classroom interaction behavior, including temporal dependencies in the time series, interaction patterns between teachers, and the long-term evolution trends of teacher behavior. Let the parameter gradient at time s be represented by $g(s)$, the second-order momentum $N(s)$ is the accumulated sum of the squared gradients, and γ is a smoothing term parameter to avoid the denominator being zero. The optimizer calculation formula is as follows:

$$
\begin{gathered}
m_s = \sqrt[\infty]{\alpha_2^{2\infty}N_{s-2} + (1-\alpha_2^{\infty})\alpha_2^{\infty}\left|g(s)\right|^{\infty} + (1-\alpha_2^{\infty})\left|g(s)\right|^{\infty}} \\
m_s = MAX\left(\alpha_2 * N_{s-1}, \left|g(s)\right|\right) \\
\Delta a = -\frac{g(s)}{m_s + \gamma} * \lambda
\end{gathered}
\tag{7}
$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

From the experimental results in Tables 1 and 2, it can be seen that the method proposed in this paper shows significant advantages in improving prediction accuracy and classroom interaction effects. In the comparative analysis of the training and validation sets, the performance of this method surpasses that of other traditional models, especially in metrics such as hits@10, hits@50, and hits@100, which are significantly higher than those of GraphSAGE, GAT, DGCNN, RGCN, SGC, and PPNP models. On the training set, this method achieves hits@10 of 24.32, hits@50 of 36.32, and hits@100 of 43.15, which is an improvement over the PPNP model (22.89, 34.52, 41.23) to varying degrees. The performance on the validation set is also excellent, with hits@10 of 33.48, hits@50 of 52.31, and hits@100 of 61.23, which is close to the performance of PPNP on the training set (33.56, 53.23, 63.21). However, in the metrics of map@10, map@50, and map@100, this method still leads with values of 21.58, 22.68, and 22.54, fully demonstrating its potential and advantages in classroom interaction behavior analysis and prediction.

Table 1. Experiment results on the training set

Training Set						
Models	**hits@10**	**hits@50**	**hits@100**	**map@10**	**map@50**	**map@100**
GraphSAGE	11.56	17.56	22.31	5.68	5.56	6.12
GAT	12.26	21.23	26.23	5.89	6.52	6.68
DGCNN	12.65	24.59	31.25	8.36	7.23	7.89
RGCN	15.23	27.69	34.56	8.42	8.89	9.23
SGC	15.46	27.13	35.23	9.23	9.23	9.87
PPNP	22.89	34.52	41.23	13.25	14.52	16.23
The Proposed Method	24.32	36.32	43.15	15.26	15.26	15.23

Table 2. Experiment results on the validation set

Validation Set						
Models	**hits@10**	**hits@50**	**hits@100**	**map@10**	**map@50**	**map@100**
GraphSAGE	11.26	23.15	32.16	7.89	8.89	8.78
GAT	23.56	42.69	51.23	11.26	12.23	12.23
DGCNN	28.54	46.23	56.48	16.23	15.26	15.23
RGCN	28.23	46.21	57.26	15.23	16.54	16.54
SGC	31.26	47.89	57.22	16.58	17.56	18.26
PPNP	33.56	53.23	63.21	21.23	22.23	22.31
The Proposed Method	33.48	52.31	61.23	21.58	22.68	22.54

Through a series of ablation experiments on the proposed model, the results shown in Figure 4 indicate that each module contributes differently to improving prediction performance. In the training set, the full model achieves 34%, 55%, and 66% in hits@10, hits@50, and hits@100, respectively, significantly outperforming other ablation versions. For example, the model using homogeneous networks only has 28%, 42%, and 50.5%, and the performance drops when the teacher-student recommendation relationship, attention relationships, or time embeddings are not considered. Specifically, without time embedding, hits@100 is 59%, while the full model improves by about seven percentage points. Similarly, compared with the model without dimensionality expansion (hits@10 is 29.5%, hits@50 is 47%, hits@100 is 59.5%), the full model improves by about 4 percentage points. In the validation set, the full model also performs excellently, with hits@10 being 24%, hits@50 being 36%, and hits@100 being 42.5%, far surpassing other versions. Overall, each optimization operation in the model, such as time embedding and dimensionality expansion, plays an active role in improving prediction accuracy.

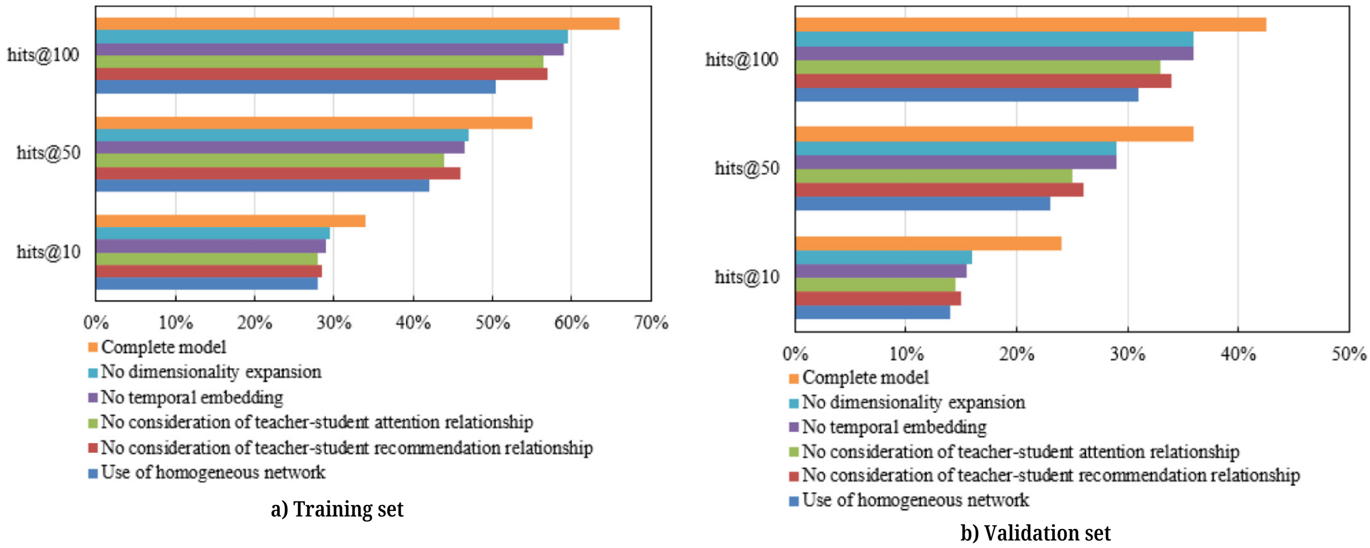

Fig. 4. Ablation experiment of the proposed model

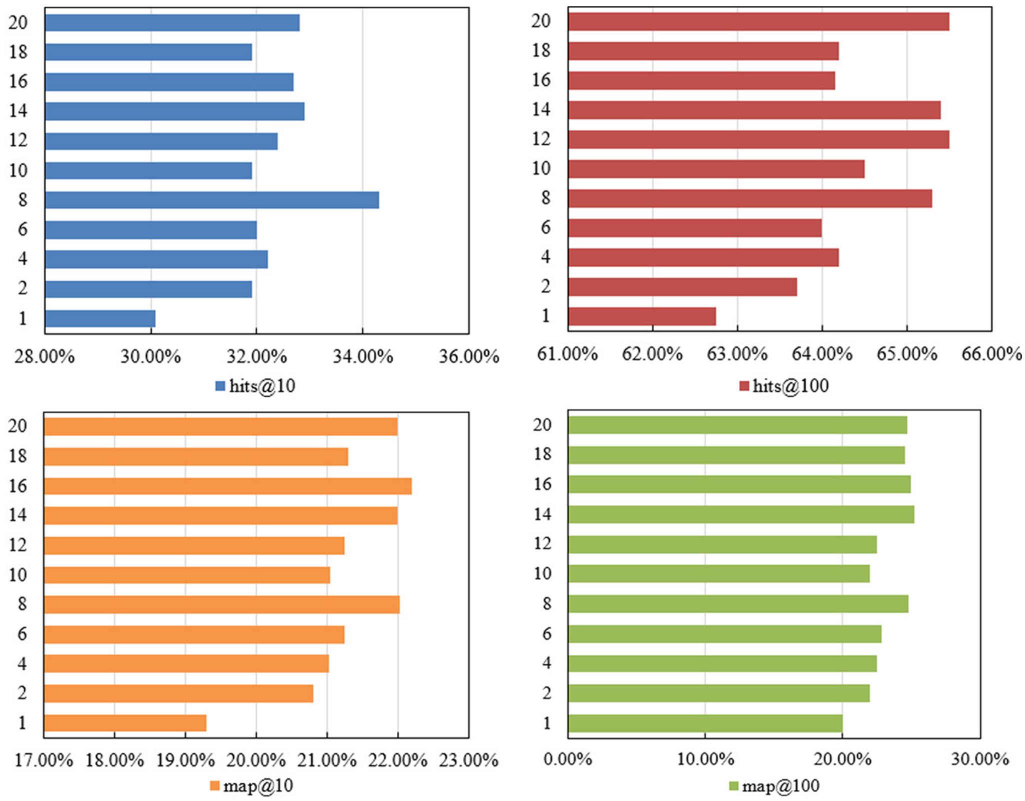

Fig. 5. Comparison and analysis of model performance metrics under different time intervals

From the data in Figure 5, it can be seen that the proposed model shows some fluctuations in prediction accuracy under different time intervals, but the overall trend is that as the time interval increases, the model performance improves significantly. For the hits@10 metric, the best performance is observed at 8 time points, reaching 34.3%, while at other shorter or longer time intervals, the performance slightly declines. Specifically, when the time intervals are 1, 2, 4, and 6, the hits@10 scores are 30.10%, 31.90%, 32.20%, and 32%, respectively. As the time interval increases, the performance gradually rises and peaks at 10, then slightly fluctuates and eventually reaches 32.80% at 20. For hits@100, the prediction accuracy generally improves with the increase in time intervals, from 62.75% (time interval 1) to 65.50% (time interval 12 and 20), showing a relatively steady growth trend. For the map@10 and map@100 metrics, as the time interval increases, the model improves from 19.30% to 22.20% (time interval 16) in map@10 and from 20.05% to 25.20% (time interval 14) in map@100, indicating that longer time intervals help improve prediction accuracy and ranking quality.

From the experimental results, it can be seen that the mobile technology method proposed in this paper not only performs excellently in improving prediction accuracy but also has significant implications for enhancing classroom interaction effects for accounting teachers in higher vocational colleges. Through data mining and prediction models, it is possible to accurately identify the interaction behaviors of teachers in different teaching situations and provide specific feedback and suggestions for teachers and educational decision-makers. The advantage of this method is its ability to comprehensively consider multi-dimensional influencing factors, thus providing more personalized and real-time analysis for teaching interaction.

5 CONCLUSION

This paper, through an in-depth analysis of the classroom interaction behavior of accounting teachers in higher vocational colleges under the mobile network environment, explored the specific performance and influencing factors of interaction behavior in different teaching situations, and based on the application of data mining and prediction models, proposed effective solutions for optimizing classroom interaction effects. The study shows that the combination of mobile technology and data mining methods can significantly improve the prediction accuracy of classroom interaction and provide strong support for educational decision-making. In the experimental results, with the optimization of time intervals and dimensionality expansion operations, the model shows outstanding performance in improving the prediction ability of teacher-student interactions, especially in improving accuracy, recall, and classroom interaction efficiency. The introduction of mobile technology effectively promotes the quality of interaction between teachers and students, leading to real-time adjustment and optimization of teaching strategies. Therefore, the research in this paper not only provides new ideas for the interaction behavior of teachers in higher vocational colleges but also provides precise data support and feedback tools for educational decision-makers, helping to improve teaching quality and student learning outcomes.

The study in this paper has significant academic value and practical application significance. First, the research fills the gap in the application of mobile technology to enhance classroom interaction, broadening the research perspective on teaching behavior analysis and educational decision-making. Second, through the proposed model and method, this paper provides a quantitative analysis tool for managing teacher interactions in universities, which can help teachers accurately grasp classroom dynamics and optimize teaching methods. However, the research also has certain limitations. Since the data mainly comes from specific higher vocational colleges, and the sample size and data types may be limited, it may not fully represent teaching scenarios in other disciplines or on a larger scale. Future research can expand in the following areas. First, the model can be further improved and optimized for different subjects and teaching scenarios, enhancing its cross-domain adaptability. Second, combining more teaching data sources, such as student emotion analysis, interaction content analysis, etc., can improve the model's precision and fine-grained analysis capabilities. Moreover, advanced artificial intelligence technologies such as deep learning can be considered to be integrated into the model to further enhance prediction performance. At the same time, the research should also focus on the real-time nature and application effect of the model, exploring how to better apply this model to daily teaching management, helping teachers receive feedback in real time and make adjustments during the teaching process, thus realizing intelligent education management. Finally, future research can explore how to combine mobile technology with other intelligent tools to promote educational model innovation and continuous improvement of teaching quality.

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