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PAPER

Application and Optimization Strategies for Teacher-Student Interaction in Language Teaching through Interactive Mobile Technology

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ABSTRACT

With the rapid development of information technology, the application of interactive mobile technology in the field of education has become increasingly widespread. In particular, optimizing the teacher-student interaction has become a key factor in enhancing teaching effectiveness in language education. Under traditional language teaching models, teacher-student interaction tends to be unidirectional, making it difficult to fully stimulate students' interest and engagement. The introduction of interactive mobile technology has made the teaching process more flexible and diverse, providing new forms and approaches for teacher-student interaction. However, how to scientifically assess and effectively optimize teacher-student interaction remains a critical issue in current educational research. Existing studies mainly focus on technological applications and lack an in-depth exploration of the essence of interaction, particularly in terms of the quantitative analysis of interaction intensity and evolution. This study aims to explore the application and optimization strategies of interactive mobile technology in teacher-student interactive language teaching. The study includes four main components: first, analyzing the evolution of teacher-student interaction in language teaching; second, calculating the intensity of teacher-student interaction based on information entropy; third, constructing and calculating a model for the evolution of interaction intensity; and fourth, proposing language teaching optimization strategies based on the evolution of teacher-student interaction intensity. This study, through theoretical modeling and empirical analysis, seeks to provide scientific evidence and practical guidance for improving the quality of teacher-student interaction and optimizing language teaching.

KEYWORDS

interactive mobile technology, teacher-student interaction, language teaching, interaction evolution, information entropy, teaching optimization strategies

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1 INTRODUCTION

In the current era of rapid technological advancement, mobile technology has pervasively infiltrated the field of education, offering new possibilities for the innovation of teaching methods [1–5]. Teacher-student interaction is a key element in language education, yet traditional teaching models often fail to meet the learning needs of modern students [6–10]. With the introduction of interactive mobile technology, the forms and content of teacher-student interaction have undergone profound changes, providing new opportunities for the optimization of language teaching [11, 12]. However, a systematic study and guidance on how to effectively utilize these technologies to enhance the quality of teacher-student interaction remain lacking.

Study on the application of interactive mobile technology in teacher-student interactive language teaching holds significant practical implications. On one hand, such technology can enhance the interactivity and engagement within the teaching process, improving students' learning outcomes [13, 14]. On the other hand, it offers teachers a convenient and efficient tool, facilitating the continuous improvement and optimization of teaching methods [15–18]. A comprehensive study of the application of interactive mobile technology in language teaching could provide educators with scientific theoretical guidance and practical solutions, promoting the development of educational informatization.

Although considerable research has focused on the application of interactive mobile technology in teaching, most studies remain confined to the technological application level, lacking an in-depth exploration of the evolution of teacher-student interaction [19–22]. Furthermore, the existing research methods for calculating teacher-student interaction intensity are insufficient, often failing to effectively reflect the complexity and dynamic nature of information transmission during interactions. These limitations hinder the practical effectiveness of interactive mobile technology in language teaching.

To address these challenges, this study investigates the application and optimization strategies of interactive mobile technology in teacher-student interactive language teaching. The study consists of four main components: first, describing the evolution of teacher-student interaction in language teaching; second, calculating the intensity of teacher-student interaction based on information entropy; third, constructing and calculating a model for the evolution of interaction intensity; and finally, proposing language teaching optimization strategies based on the evolution of teacher-student interaction intensity. Through systematic analysis and model construction, this study aims to provide a scientific and effective strategy for optimizing language teaching, offering both theoretical foundations and practical guidance for enhancing teacher-student interaction quality and teaching effectiveness.

2 DESCRIPTION OF TEACHER-STUDENT INTERACTION EVOLUTION IN LANGUAGE TEACHING

In the process of language teaching, teacher-student interaction is a critical factor determining the effectiveness of teaching. Traditional research on teacher-student interaction has predominantly focused on static analysis, often employing binary relationship models, which assess the extent of interaction solely based on frequency or temporal dimensions. This approach overlooks the dynamic changes in teacher-student interaction relationships. However, the actual interaction in language teaching is complex and dynamic, particularly in the context of interactive mobile technology, where teacher-student interaction is influenced by multiple factors, such as time and space. In location-based interactive mobile networks, teacher-student interaction is not only affected by physical location but is also closely related to the time at which the interaction occurs. For instance, in the same location and time, the frequency of teacher-student interaction can reflect the intensity of their language teaching relationship. In contrast, prolonged periods of no interaction may lead to the alienation of this relationship. Therefore, teacher-student interaction should be regarded as an evolving process, influenced by both time and space, rather than a static binary relationship.

Based on these characteristics, the definition of teacher-student interaction evolution proposed in this study aims to analyze the interaction process between teachers and students at different times and locations using interactive mobile technology as well as quantify the intensity of interaction and its evolution. Specifically, by collecting check-in data from users of interactive mobile networks, including location and time information, this study extracts the interaction sequences between teachers and students and calculates the interaction intensity at each moment and location. This intensity value reflects not only the frequency of interaction but also reveals the depth and variation in the interaction relationship. Specifically, for a set of interactive mobile network users, denoted as $I = \{i_1, i_2, \ldots, i_v\}$, their check-in records can be represented as a tuple of the form $<i, m, s>$. Figure 1 shows the overall framework for analyzing the evolution of teacher-student interaction intensity.

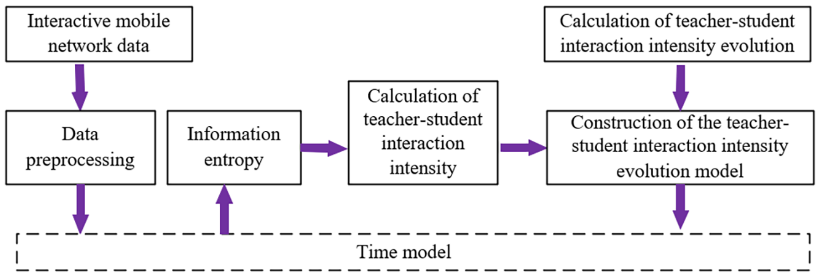

Fig. 1. Overall framework for analyzing the evolution of teacher-student interaction intensity

3 CALCULATION OF TEACHER-STUDENT INTERACTION INTENSITY BASED ON INFORMATION ENTROPY

With the rapid development of mobile communication technology and smart devices, interactive mobile networks have provided a new platform for establishing more flexible and efficient language-teaching interactions between teachers and students. In this network environment, teacher-student interaction is no longer solely reliant on face-to-face communication in traditional classroom settings but can also occur at any time and place through mobile devices. As the frequency, time, and space of interaction vary, the interaction intensity of the teacher-student language teaching also undergoes dynamic changes. The language teaching interaction intensity is an important indicator for measuring the closeness of teacher-student relationships and the frequency of interaction. It reflects the level of cooperation and engagement between teachers and students in the language teaching process. Traditional static analysis methods are unable to accurately reveal such dynamic changes. However, based on the temporal diversity and dynamic characteristics of interaction behaviors in interactive mobile networks, a new analytical perspective is provided. This study quantifies the interaction intensity through the temporal diversity of teacher-student interaction sequences, aiming to uncover the trends of interaction changes during different time periods, thereby providing scientific evidence for optimizing teaching strategies and improving teaching quality. Figure 2 shows the diagram of the time model for teacher-student interaction relationships.

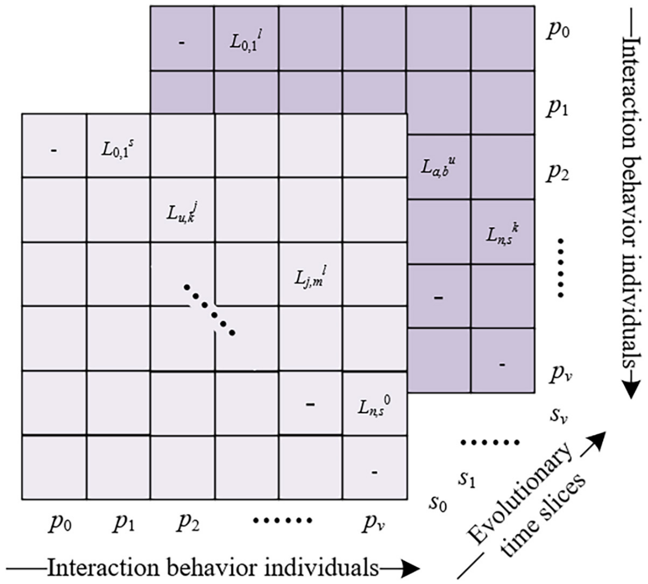

Fig. 2. Diagram of the time model for teacher-student interaction relationships

In language teaching, the teacher-student interaction relationship is a complex and dynamic process. Over time, the frequency, quality, and modes of interaction between teachers and students continuously evolve. To accurately capture this process of change, it is essential to consider the influence of time on the intensity of the language teaching interaction relationship. Therefore, this study constructs a calculation framework for interaction intensity based on the time model by processing the time diversity of teacher-student interaction sequences. By refining the temporal granularity and decomposing the interaction data into multiple time segments, the teacher-student interactions within each segment can be analyzed independently. Each time segment represents a "static" state, in which the teacher-student interaction relationship is treated as a fixed, quantifiable intensity value. By integrating interaction data across different time segments, the evolutionary process of the teacher-student interaction relationship can be comprehensively reflected, revealing the trends in the relationship as it develops over time. In constructing the time model, a time series feature analysis based on check-in data was employed in this study. Each check-in record was considered an interaction activity, and these activities were categorized into different time segments in chronological order. In each time segment, the interaction intensity between teachers and students was quantified and organized into a two-dimensional matrix. Each value in the matrix represents the interaction intensity between a specific teacher and student at a given moment. To better capture dynamic changes, a time granularity parameter was defined, which divides the check-in data evenly into several time periods. Each time period corresponds to a "local static" calculation of interaction intensity. Finally, by combining the interaction intensity across the various time segments, a time model was constructed that dynamically presents the evolution of teacher-student interaction intensity.

Within this study framework, the time interaction vector serves as a key tool for quantifying the interaction frequency between teachers and students during specific time periods. Specifically, the time interaction vector $S_{(u,k)}$ was used to represent the number of encounters between interactive mobile network users u and k over a time span of V days, segmented according to a particular granularity. Time was divided into V/s fixed time intervals, where s is the granularity unit, and each time period recorded the interaction events—i.e., the matching of check-in records—within that interval.

For each teacher-student pair, the diversity of the time interaction vector $S_{(u,k)}$ reflects the stability and intimacy of their interactions. If the interaction frequency is evenly distributed across multiple time segments, this suggests that the teacher-student interaction is sustained and stable, likely indicating a close relationship. In contrast, if all interactions are concentrated within a few time segments, it suggests that the interaction relationship is sporadic, and its intensity is relatively weak. The encounter between u and k in region m and time segment s can be represented by the following equation:

$$e_{u,k,m,s} = \langle u,k,m,s \rangle \tag{1}$$

The encounters between u and k over all time segments can be represented as:

$$E_{u,k} = \bigcup_{k=1}^{V/s} e(e,k,m,s) \tag{2}$$

The probability of a teacher-student encounter from the set $E_{(u,k)}$ occurring within time segment s can be computed using the following equation:

$$O_{(u,k,s)} = \frac{\left|E_{(u,k,s)}\right|}{\left|E_{(u,k)}\right|} \tag{3}$$

In information theory, Shannon entropy is used to measure the uncertainty of a random variable. The higher the entropy value, the greater the uncertainty of the variable and the higher the information content. In this study, a higher entropy value for the time interaction vector indicates that the interactions between the teacher and student are more evenly distributed and dispersed across different time segments. Such an interaction relationship is typically closer and more stable. Conversely, a lower entropy value indicates that the interactions are more concentrated, which may be coincidental or sporadic, suggesting a weaker interaction intensity. The uncertainty of the time period of a randomly selected encounter event from set E is defined by the following equation:

$$G^{T}_{(u,k)} = -\sum_{s} \left(O_{(u,k,s)} \log O_{(u,k,s)} \right) \tag{4}$$

$$F = \exp(G) \tag{5}$$

In the proposed method for calculating teacher-student interaction intensity, the diversity F serves as a key indicator of the breadth of the interaction frequency distribution between the teacher and student. The formula for diversity is given above. Diversity reflects the temporal distribution of interactions between users in the interactive mobile network, i.e., whether their interactions are evenly distributed across various time segments or concentrated within specific time periods. Specifically, if the interaction frequency between two interactive mobile network users is distributed across multiple time intervals over a long period, their interaction relationship exhibits higher diversity. In contrast, if their interactions are concentrated in only a few time segments, particularly within a single time period, the diversity of this interaction relationship is low.

In the context of language teaching, teacher-student interactions often exhibit strong temporal concentration or periodicity. This is typically the case when teachers and students share fixed schedules or engage in joint public activities. For example, if encounters between the teacher and students occur predominantly within specific time periods, such as during collective activities on certain days or regular class schedules, this is likely determined by pre-set teaching plans or shared course arrangements. Although these interactions are still valid, the high regularity and concentration of their timing reflect systemic arrangements or external factors, rather than naturally occurring, flexible, and spontaneous interactions. Therefore, while these interaction events can still provide some information about teacher-student interaction relationships, their impact on the actual language teaching outcomes or interaction quality is limited. As such, during the calculation process, relatively less weight should be assigned to these time interaction vectors. To address this, Renyi entropy was further employed to calculate the diversity of time interaction vectors between teacher and student in the interactive mobile network.

$$G_{uk}^{E} = \left(-\log \sum_{u} {O_{(u,k)}^{s}}^{w} \right) \Big/ (w-1) \tag{6}$$

Where w represents the diversity order, which characterizes the sensitivity of the diversity of the teacher-student interaction time distribution to interaction frequency. The corresponding diversity of the time interaction vector can be calculated using the following equations:

$$E_{uk} = \exp\left(G_{uk}^{E}\right) \tag{7}$$

$$E_{uk} = \exp\left[\left(-\log \sum_{u} O_{(u,k)}^{s} \right) \Big/ (w-1) \right] \tag{8}$$

When $w > 1$, a higher local encounter frequency $e_{u,k,m,s}$ contributes more significantly to the Renyi entropy. As $w \to 1$, then $E \to G$. The teacher-student language teaching interaction intensity t is a linear function of time diversity, and the specific equation is as follows:

$$t_{uk} = \Psi(E_{uk}) \tag{9}$$

4 CONSTRUCTION AND CALCULATION OF THE TEACHER-STUDENT INTERACTION INTENSITY EVOLUTION MODEL

The Ebbinghaus forgetting curve suggests that human memory of information gradually declines over time, with a rapid initial rate of forgetting. This theory can be applied to the teacher-student interaction relationship in language teaching, as not all past interactions exert the same influence on the current teaching relationship. Recent interactions are more likely to have a profound impact on the current teacher-student interaction, while earlier interactions may diminish in influence over time. Additionally, in language teaching interactions, the frequency and quality of interactions between teachers and students are influenced by various factors, such as changes in teaching content, adjustments in learning progress, and interactive activities. These factors evolve over time, with recent interactions often more reflective of the current teaching relationship. The Ebbinghaus forgetting curve was employed in this study to model the temporal decay of historical interaction information. By weighting interaction data at different time points, a more accurate evaluation of the actual intensity of teacher-student interaction can be achieved.

The interest drift model addresses another critical dimension of teacher-student interaction relationships: the evolution of interest. In language teaching, interaction relationships are influenced not only by time but also by the shifting interests of both teachers and students. These interests may change over time and under varying circumstances, directly affecting interaction choices and frequencies. By integrating the interest drift model, the calculation model can dynamically adjust the interaction intensity to reflect the impact of these changes in interest. The decay coefficient of teacher-student interaction intensity is denoted by μ, while the times of the first and last interactions are represented by s_{KS} and s_{JS}, respectively. Based on the evolution characteristics of teacher-student interaction intensity, the following decay function was introduced:

$$DE(s_u) = 1 - \mu + \mu\left(\frac{s_u - s_{KS}}{s_{JS} - s_{KS}}\right)^2 \tag{10}$$

The equation below presents the calculation method for the evolution of the teacher-student language teaching interaction relationship. Figure 3 shows the teacher-student interaction intensity evolution model.

$$TR_u = \varepsilon\left(\frac{t_u * DE\left(s_u\right) + t_p}{t_p}\right)^2 - \varepsilon \tag{11}$$

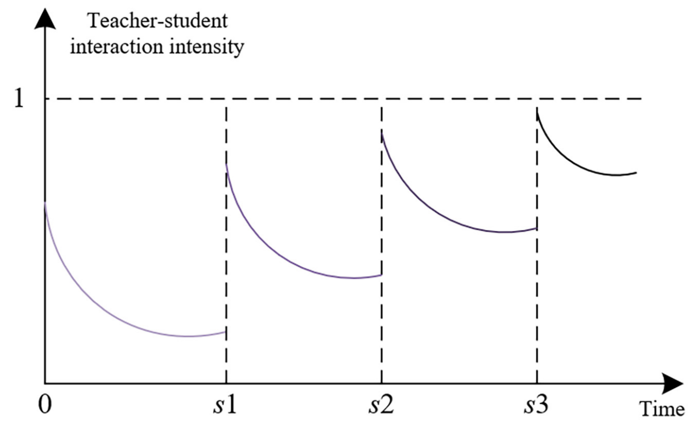

Fig. 3. Teacher-student interaction intensity evolution model

5 LANGUAGE TEACHING STRATEGY OPTIMIZATION SCHEMES BASED ON THE EVOLUTION OF TEACHER-STUDENT INTERACTION INTENSITY

Building upon the aforementioned computational model based on the forgetting curve and interest drift, several language teaching strategy optimization schemes were proposed, aiming to enhance the interaction efficiency between teachers and students and increase the interactivity and personalization of teaching:

a) Personalized teaching content delivery based on the dynamic interest model: By analyzing the interest drift characteristics within the teacher-student interaction relationship, changes in students' interests throughout the language learning process can be identified. Consequently, the teaching content can be dynamically adjusted. Teachers can leverage interactive mobile network platforms to deliver personalized teaching content that aligns with students' current interests and learning progress.

b) Balancing interaction frequency and quality: According to the principles of the Ebbinghaus forgetting curve, students' memory of knowledge gradually declines over time. Therefore, teachers should design periodic review tasks to prevent students from forgetting key content. At the same time, considering the impact of interest drift, teachers can monitor changes in students' interests via interactive mobile network platforms and adjust interaction frequencies in a timely manner.

c) Optimizing interaction intensity assessment using historical data: By utilizing historical interaction data and interest changes, teachers can assess each student's learning progress and interaction intensity. Through the combined application of the forgetting curve and interest drift evolution calculations, teachers can obtain real-time insights into students' learning attitudes and engagement levels, thereby optimizing interaction strategies. Real-time assessment and analysis of teacher-student interaction intensity enable teachers to promptly adjust the pace and methods of instruction, improving the adaptability of teaching.

d) Integration of contextual learning and periodic review: Based on location-based interactive mobile network data, teachers can design contextual learning tasks according to students' geographical locations and learning progress. For instance, when students are in the classroom, extracurricular settings, or specific learning environments, teachers can use geolocation technology to push relevant learning tasks to students, enhancing the immediacy and practicality of the learning process. At the same time, teachers should design periodic review mechanisms through timely review tasks based on the decay pattern of the forgetting curve, thereby ensuring long-term retention of key knowledge. By integrating contextual learning with periodic review, teachers can better stimulate students' interest and maintain their continuous engagement with the learning content.

e) Interactive feedback and continuous adjustment: The interaction between teachers and students is reflected not only in interaction frequency but also in interaction quality and feedback mechanisms. Teachers can use interactive platforms to provide instant feedback, thereby enhancing students' sense of participation. In conjunction with the evolution model of interaction intensity, teachers can analyze students' feedback to evaluate their level of engagement and understanding, facilitating timely adjustments to teaching strategies.

f) Relationship building between teachers and students: By observing the evolution of teacher-student interaction relationships, teachers can further adjust their communication methods and emotional connections with students. For example, when a teacher identifies that a student's interest in the content has diminished over a period, personal communication can be initiated to understand the student's changing interests or learning challenges, thereby offering personalized support.

6 EXPERIMENTAL RESULTS AND ANALYSIS

From the experimental data in Figures 4 and 5, it can be observed that as the diversity order increases, the precision in the Coursera MOOC and Duolingo datasets exhibits certain fluctuations at different recall rates. In the Coursera MOOC dataset, at a recall rate of 20%, the precision remains at a relatively high and stable level with an increase in the diversity order (ranging from 0.92 to 0.9). However, as the recall increases (e.g., at recall rates of 70% and 80%), the precision significantly declines, particularly at a recall rate of 80%, where the precision drops to 0.65. In contrast, the precision in the Duolingo dataset shows a more stable fluctuation at higher diversity orders, with high precision maintained across various recall rates. For example, at a recall rate of 20%, the precision remains around 0.95, gradually decreasing but still remaining within the range of 0.6–0.7 at an 80% recall rate, indicating a more stable interaction pattern and stronger content diversity in the teaching model. Therefore, although precision decreases at higher diversity orders, the datasets from the two platforms display differing adaptability and distinct precision fluctuations. This suggests that these differences should be considered when designing interactive language teaching strategies in order to optimize teacher-student interactions more effectively.

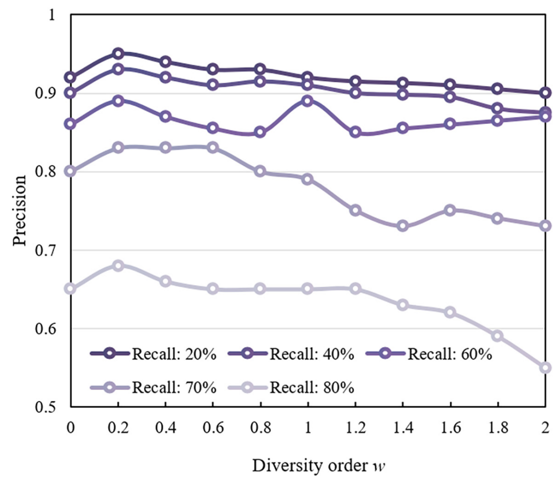

Fig. 4. Diversity order and precision in the Coursera MOOC dataset

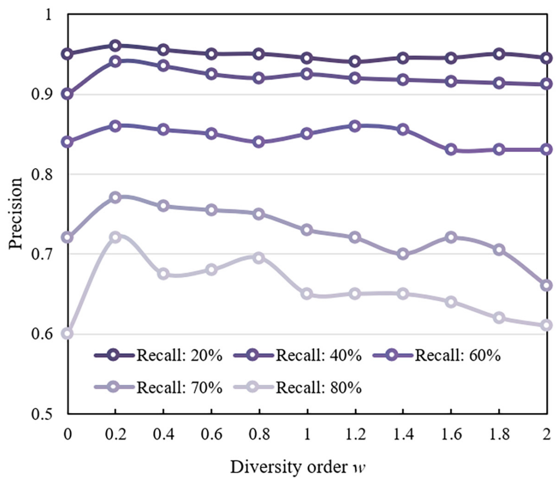

Fig. 5. Diversity order and precision in the Duolingo dataset

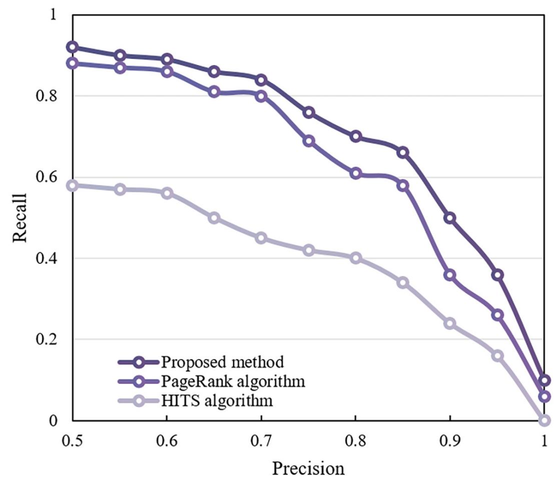

Fig. 6. Precision and recall in the Coursera MOOC dataset

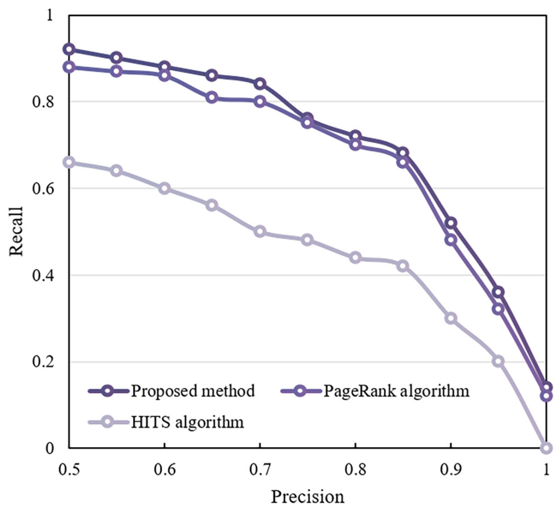

Fig. 7. Precision and recall in the Duolingo dataset

The experimental data from Figures 6 and 7 reveal significant differences in the precision and recall performances across the various algorithms for the Coursera MOOC and Duolingo datasets. As precision and recall increase, distinct trends emerge in the performance of the algorithms. In the Coursera MOOC dataset, the proposed method demonstrates superiority over the PageRank and hyperlink-induced topic search (HITS) algorithms in both precision and recall, particularly maintaining more stable performance at higher precision levels. For example, when precision is 0.9, the proposed method achieves 0.84, while PageRank reaches 0.8 and HITS is only 0.45. However, as precision gradually decreases and drops to 0.5, the proposed method achieves 0.7, PageRank attains 0.61, and HITS only reaches 0.4. This highlights the method's advantages, maintaining relatively high precision while adapting well to complex situations. In the Duolingo dataset, although all algorithms show a slight decrease in precision and recall, the proposed method still outperforms both the PageRank and HITS algorithms in overall precision, particularly at higher recall rates. For instance, at a precision of 0.8, the proposed method achieves 0.86, while PageRank reaches 0.81, and HITS only 0.56. Overall, the proposed method exhibits higher precision and greater adaptability compared to the other two algorithms, especially in complex teacher-student interaction models, effectively enhancing the precision and operability of teaching strategies.

Based on the above experimental results, the proposed method shows clear advantages over the PageRank and HITS algorithms in both precision and recall, particularly in its application across different teaching environments. This demonstrates its capacity to effectively adapt to complex teacher-student interaction patterns while maintaining high precision. This finding is significant for constructing and optimizing the teacher-student interaction evolution model. First, the intensity of teacher-student interaction evolves over time and with the diversification of information exchange, requiring teachers to precisely control the complexity of interactions to avoid either information overload or deficiency. When optimizing the teaching strategies, the proposed method allows for the intelligent adjustment of interaction intensity and content, based on changes in precision and recall, to maintain optimal teaching effectiveness. This strategy optimization can help teachers dynamically adjust teaching strategies in various teaching contexts, improving student learning efficiency and enhancing the quality of teacher-student interaction, thereby better fostering the depth and breadth of language learning.

Table 1. Comparison of teacher-student interaction intensity in language teaching

Time	User (10, 11)			User (20, 21)		
	Proposed Method	Pagerank Algorithm	Hits Algorithm	Proposed Method	Pagerank Algorithm	Hits Algorithm
0	1	No	No	1	No	No
1	0.66254	0	0	0.95621	0.62354	0.66521
2	0.71542	0	0	0.84521	0.74512	0.77853
3	0.81235	0	0	0.66235	0.73265	0.74512
4	0.83254	0	0	0.62152	0	0
5	0.92365	0.66524	0.71245	0.61256	0	0
6	0.82356	0.71256	0.77895	0.58956	0	0
7	0.71245	0.75468	0.73256	0.55213	0	0
8	0.55869	0.62355	0.73526	0.62335	0	0

The data displayed in Table 1 shows a clear difference in the performance of the proposed method, the PageRank algorithm, and the HITS algorithm at various time points, with significant variations in the interaction intensity between users (10, 11) and (20, 21). Starting from time 0, the interaction intensity between users (10, 11) and (20, 21) gradually changes. For user (10, 11), the proposed method demonstrates a clear upward trend. Between time 1 and time 5, the interaction intensity increases from 0.66254 to 0.92365, while the PageRank and HITS algorithms show more stable or decreasing trends. Notably, at time 5, the interaction intensity of both the PageRank and HITS algorithms does not exceed 0.71245 (PageRank) and 0.71256 (HITS), respectively. For user (20, 21), although the interaction intensity of the proposed method is relatively low at earlier time points (e.g., time 1, time 2), it begins to show a strong growth trend in the later stages (e.g., at time 5 and time 6), ultimately reaching 0.62335 at time 8, significantly higher than the interaction intensity of both the PageRank and HITS algorithms. Overall, the proposed method demonstrates superior interaction intensity evolution compared to the other algorithms at all time points. It effectively enhances teacher-student interaction intensity, particularly in more complex teaching scenarios, where it continuously optimizes the interaction model between teachers and students.

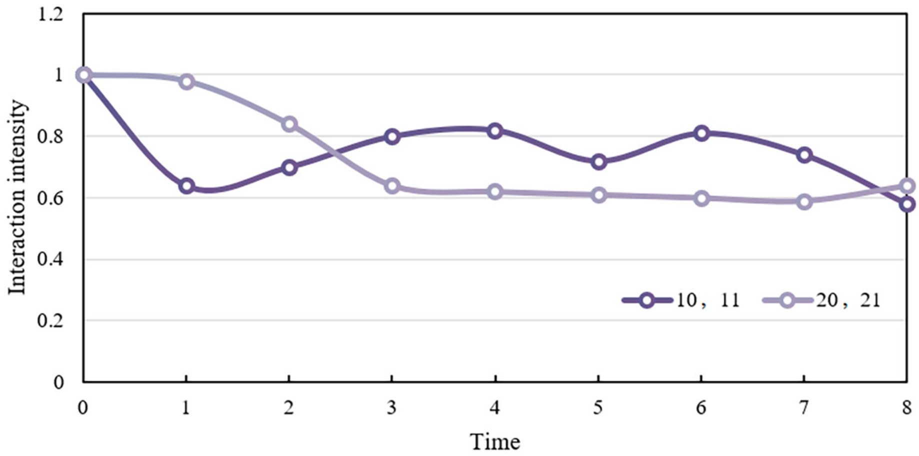

Fig. 8. Evolution of teacher-student interaction intensity in language teaching

The data presented in Figure 8 illustrates the distinct differences and dynamic changes in the teacher-student interaction intensity between users (10, 11) and (20, 21) across various time points. For user (10, 11), despite the initial interaction intensity being 1, there is a gradual decline over time, with particularly noticeable fluctuations after time 5. Specifically, the interaction intensity for user (10, 11) rises from 0.64 at time 1 to 0.82 at time 4, but then a clear downward trend is observed, with the intensity dropping to 0.58 by time 8. In contrast, the interaction intensity for user (20, 21) remains relatively stable. Although it reaches a high value of 0.98 at time 1, it gradually declines, only to rise again to 0.64 by time 8. Overall, the interaction intensity of user (20, 21) shows a higher degree of stability in the early stages, gradually stabilizing as time progresses, while the interaction intensity of user (10, 11) exhibits more significant fluctuations, particularly with a downward trend in the later stages. These findings reflect the complexity and dynamic nature of teacher-student interactions, highlighting the differences in interaction processes between different learners.

Based on the experimental data, the following important conclusions can be drawn: The intensity of teacher-student interactions throughout the teaching process demonstrates an evolving characteristic, and this evolutionary process significantly impacts the optimization of language teaching strategies. For user (10, 11), although the interaction intensity increases during the early stages, indicating relatively active initial interactions, the decline in interaction intensity over time may reflect the students' adaptation to the learning content and potential fatigue with the teaching model. This dynamic change suggests that teachers must adjust their teaching strategies in a timely manner, such as by increasing the diversity of interactions or adopting more flexible teaching methods, in order to sustain students' interest and engagement. For user (20, 21), the interaction intensity remains relatively stable. Despite initially stronger interactions, the trend gradually stabilizes, which may indicate that this learner group is more stable during the teaching process, with their interaction intensity being more influenced by external factors, such as the teaching content and interaction formats. The teacher-student interaction intensity evolution model can assist teachers in better identifying students' learning states and interaction patterns. By adjusting interaction intensity and content in real time, it is possible to avoid information overload or the monotony of teaching content, thereby optimizing teaching strategies and enhancing student learning outcomes. Through the effective control of dynamic interaction changes, teachers can provide more personalized and adaptive teaching services, improving teaching quality and student engagement.

7 CONCLUSION

Optimization schemes for language teaching strategies, based on the evolution of teacher-student interaction intensity, were proposed in this study by investigating the application of interactive mobile technology in teacher-student interactive language teaching. It was found that by dynamically adjusting the intensity of teacher-student interaction relationships, significant improvements in student participation and learning efficiency can be achieved. Experimental results indicate that teachers can avoid the decline in learning interest caused by insufficient interaction intensity or the information overload associated with excessive interaction by flexibly adjusting teaching strategies. By monitoring and optimizing the teacher-student interaction intensity in real time, teachers are able to more precisely identify students' learning needs, adjust teaching content, and regulate interaction frequency, thereby enhancing teaching quality. In summary, this study not only provides new insights into the application of interactive mobile technology in language teaching but also introduces a scientifically sound and effective method for optimizing teaching strategies. This method holds significant theoretical value and practical application potential.

However, certain limitations remain in this study. The study primarily focuses on the Coursera MOOC and Duolingo datasets, which, although representative, are limited to specific online education platforms and language learning contexts and do not comprehensively cover other fields and teaching environments. Furthermore, the proposed method may be influenced by the data volume and quality in more complex teaching environments, leading to potential uncertainties in its application within large-scale classrooms. Future research could explore the following directions: First, the scope of datasets could be expanded to include a wider range of online learning platforms and diverse language teaching contexts, thereby verifying the universality and adaptability of the proposed method. Second, more teaching factors could be incorporated to further optimize the calculation model of teacher-student interaction intensity, improving the model's precision and practicality. Additionally, future studies could investigate how the optimization strategies presented in this study could be integrated with other educational technologies, such as intelligent learning systems and data mining, to provide more intelligent and personalized language teaching services.

8 REFERENCES

[1] S. Sakulwichitsintu, "Mobile technology – An innovative instructional design model in distance education," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 7, pp. 4–31, 2023. https://doi.org/10.3991/ijim.v17i07.36457

[2] B. L. Hwang, T. C. Chou, and C. H. Huang, "Actualizing the affordance of mobile technology for mobile learning," *Educational Technology & Society*, vol. 24, no. 4, pp. 67–80, 2021. https://www.jstor.org/stable/48629245

[3] X. Yu and D. Yang, "The influence of mobile technology on STEM education student learning outcomes," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 20, pp. 37–50, 2024. https://doi.org/10.3991/ijim.v18i20.50837

[4] S. Criollo-C, A. Guerrero-Arias, Á. Jaramillo-Alcázar, and S. Luján-Mora, "Mobile learning technologies for education: Benefits and pending issues," *Applied Sciences*, vol. 11, no. 9, p. 4111, 2021. https://doi.org/10.3390/app11094111

[5] J. D. Bodapati and R. Konda, "Augmenting diabetic retinopathy severity prediction with a dual-level deep learning approach utilizing customized MobileNet feature embeddings," *Acadlore Transactions on AI and Machine Learning*, vol. 2, no. 4, pp. 182–193, 2023. https://doi.org/10.56578/ataiml020401

[6] M. Xiang, F. Mao, and L. Xiao, "A study on the integration of digital language teaching system into English teaching," *Journal of Computational Methods in Sciences and Engineering*, vol. 23, no. 2, pp. 913–920, 2023. https://doi.org/10.3233/JCM-226491

[7] M. M. M. A. Latif and M. M. Alhamad, "Emergency remote teaching of foreign languages at Saudi universities: Teachers' reported challenges, coping strategies and training needs," *Education and Information Technologies*, vol. 28, pp. 8919–8944, 2023. https://doi.org/10.1007/s10639-022-11512-8

[8] T. Wang, "A blended collaborative teaching mode in language learning based on recommendation algorithm," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 23, pp. 111–126, 2021. https://doi.org/10.3991/ijet.v16i23.27253

[9] L. I. Jin, Y. Xu, E. Deifell, and K. Angus, "Emergency remote language teaching and US-based college-level world language educators' intention to adopt online teaching in postpandemic times," *The Modern Language Journal*, vol. 105, pp. 412–434, 2021. https://doi.org/10.1111/modl.12712

[10] S. Mozaffari and H. R. Hamidi, "Impacts of augmented reality on foreign language teaching: A case study of Persian language," *Multimedia Tools and Applications*, vol. 82, pp. 4735–4748, 2023. https://doi.org/10.1007/s11042-022-13370-5

[11] S. Al-Amri, S. Hamid, N. F. M. Noor, and A. Gani, "A framework for designing interactive mobile training course content using augmented reality," *Multimedia Tools and Applications*, vol. 82, pp. 30491–30541, 2023. https://doi.org/10.1007/s11042-023-14561-4

[12] S. Chen and J. Wang, "Virtual reality human–computer interactive English education experience system based on mobile terminal," *International Journal of Human–Computer Interaction*, vol. 40, no. 13, pp. 3560–3569, 2024. https://doi.org/10.1080/10447318.2023.2190674

[13] X. Wang, "A study of the teacher-student interaction in a flipped classroom of college oral English based on mobile learning," *International Journal of Continuing Engineering Education and Life Long Learning*, vol. 32, no. 6, pp. 778–795, 2022. https://doi.org/10.1504/IJCEELL.2022.126859

[14] P. Zhang and X. Chang, "The influence of online teaching interactive behaviors on sustained learning results of learners," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 17, no. 10, pp. 173–185, 2022. https://doi.org/10.3991/ijet.v17i10.30941

[15] Z. Zhan, Q. Wu, Z. Lin, and J. Cai, "Smart classroom environments affect teacher-student interaction: Evidence from a behavioural sequence analysis," *Australasian Journal of Educational Technology*, vol. 37, no. 2, pp. 96–109, 2021. https://doi.org/10.14742/ajet.6523

[16] Y. Bai, "An analysis model of college English classroom patterns using LSTM neural networks," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–10, 2022. https://doi.org/10.1155/2022/6477883

[17] J. Li and H. Chen, "Construction of case-based oral English mobile teaching platform based on mobile virtual technology," *International Journal of Continuing Engineering Education and Life Long Learning*, vol. 31, no. 1, pp. 87–103, 2021. https://doi.org/10.1504/IJCEELL.2021.111837

[18] P. Zhou, "Construction of public English curriculum system based on cloud interactive teaching mode and cloud computing," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–10, 2022. https://doi.org/10.1155/2022/2534462

[19] M. Kesler, A. Kaasinen, and A. Kervinen, "Teaching science outdoors: Supporting pre-service teachers' skill development with the help of available mobile applications," *Education Sciences*, vol. 14, no. 11, p. 1218, 2024. https://doi.org/10.3390/educsci14111218

[20] W. Wang, "College English teaching platform optimization under cross-media and mobile internet environment," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–11, 2022. https://doi.org/10.1155/2022/9672463

[21] P. Zhang and X. Chang, "The influence of online teaching interactive behaviors on sustained learning results of learners," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 17, no. 10, pp. 173–185, 2022. https://doi.org/10.3991/ijet.v17i10.30941

[22] S. Chen and J. Wang, "Virtual reality human–computer interactive English education experience system based on mobile terminal," *International Journal of Human–Computer Interaction*, vol. 40, no. 13, pp. 3560–3569, 2024. https://doi.org/10.1080/10447318.2023.2190674

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