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PAPER

Innovative Applications and Teaching Effectiveness Analysis of Interactive Mobile Technology in Music Education

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ABSTRACT

With the rapid advancement of mobile Internet technology, the application of interactive mobile technology in education has emerged as a significant area of research, particularly in music education. Mobile technology has introduced transformative changes to both learning styles and teaching methods. Through the utilization of smart devices and mobile platforms, students are provided with personalized and flexible learning environments for music education, while teachers can leverage advanced technological tools to enhance teaching effectiveness. Although previous studies have examined the role of mobile technology in music education, most have focused on its isolated effects, neglecting a systematic analysis of the evolution of teaching effectiveness over time. Furthermore, existing methodologies often fail to account for temporal characteristics and dynamic changes, resulting in an incomplete evaluation of long-term educational outcomes. This study aims to analyze the network characteristics of interactive mobile technology applied in music education and to explore the evolution of teaching effectiveness with consideration of temporal characteristics. This study is expected to offer novel theoretical perspectives for the digital transformation of music education along with practical guidance for its implementation.

KEYWORDS

interactive mobile technology, music education, teaching effectiveness, temporal characteristics, teaching evolution, network characteristics

1 INTRODUCTION

In the digital era, the rapid development of mobile technology has driven unprecedented transformations in the field of education [1–4]. Particularly in music education, the application of interactive mobile technology has transcended the limitations of traditional teaching models and created extensive opportunities for innovation in instructional content and methods [5–8]. With the widespread adoption of

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smart devices, mobile technology has enabled students to experience personalized and flexible learning environments while providing teachers with more efficient teaching tools [9–11]. Consequently, exploring innovative applications of interactive mobile technology in music education holds significant practical importance.

The primary significance of this study lies in analyzing the application of interactive mobile technology in music education to uncover its profound impact on teaching effectiveness. A systematic exploration of this topic is expected to provide theoretical support for the modernization of music education and serve as a data foundation for policy formulation and technology dissemination. Furthermore, this study aims to offer new perspectives and practical insights into optimizing teaching strategies for music teachers and learning habits for students, thereby advancing music education towards greater flexibility and personalization.

However, existing research predominantly focuses on the isolated effects of mobile technology, lacking in-depth analyses of its long-term impact and evolutionary mechanisms in music education [12–15]. Current study methodologies heavily rely on traditional experimental comparisons and often fail to adequately consider temporal characteristics and the evolving nature of the teaching process. This limitation has hindered accurate assessments of the long-term effects of technological applications [16–22]. In particular, the precise evaluation of the combined impacts of teaching strategies and technology remains an unresolved challenge.

This study is structured around two primary areas of focus: first, the network characteristics of interactive mobile technology in the context of music education, examining how different network characteristics enhance learning experiences; and second, the temporal characteristics of teaching effectiveness evolution in music education, exploring the process of its dynamic changes. Through a thorough analysis of these challenges, the study not only contributes novel perspectives to academic research but also provides practical guidance for educators, facilitating the effective application and continuous optimization of interactive mobile technology in music education.

2 INTERACTIVE MOBILE NETWORK CHARACTERISTICS IN MUSIC EDUCATION

Music education, as a form of artistic education, is not only a process of knowledge acquisition but also a dynamic skill development process. In this process, student engagement, interactivity, and feedback mechanisms play crucial roles. Interactive mobile technology offers a variable learning environment for music education, allowing students to interact with teachers or peers at any time and from any location through smart devices for music learning and practice. Therefore, it can be inferred that in a mobile learning environment for music, students' learning states and progress continuously evolve over time, with each stage of learning potentially exhibiting different interaction patterns. For instance, in the early stages, students may rely more on teacher guidance and peer collaboration, whereas in later stages, individual practice and independent creation may become the dominant modes of interaction.

For the reasons outlined above, a network model based on activity-first selection was adopted in this study. This model prioritizes the connection and enhancement of nodes that exhibit frequent interaction and higher levels of participation during the learning process, thereby simulating the real dynamics of learning and teaching. This approach also allows for the precise capture of the dynamic changes in interaction patterns, enabling an analysis of how interactive mobile technology affects teaching effectiveness at different stages of learning. Figure 1 illustrates a schematic representation of the driving mechanism of the interactive mobile network based on node activity levels.

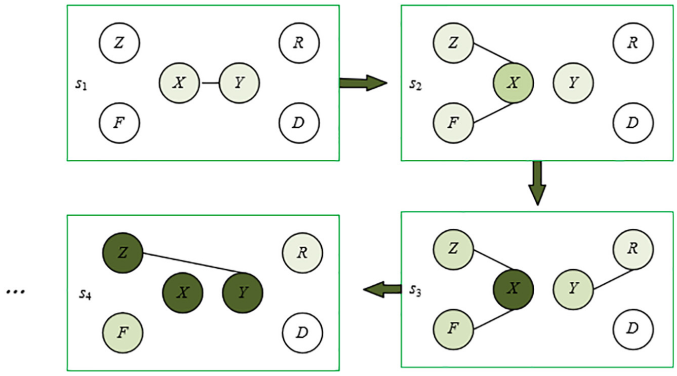

Fig. 1. Schematic representation of the interactive mobile network driving mechanism based on node activity levels

The definition of the rate of change in node activity is critical within the constructed interactive mobile temporal network. This parameter reflects the dynamic variations in interaction patterns and activity levels of students during the music learning process with other learning nodes. In the context of music education, node activity levels can be understood as the frequency of interactions by students during a specific learning phase, including activities such as participating in class discussions, engaging in self-practice, and collaborating with teachers or peers. To quantify the dynamic change, the rate of change in node activity, denoted as $j_u(S)$, was defined as the probability that node u establishes new connections with other nodes within a unit of time. This probability represents the tendency of students, based on their level of activity during a specific period, to proactively exchange knowledge or information with other learning resources such as teachers, platforms, and peers. Assuming that the total number of network nodes is represented by V, and the number of nodes participating in the teaching process is represented by l, the following equation was derived:

$$\frac{dj_u(S)}{dS} = \frac{l}{v} + \frac{lj_u(S)}{\sum_{k=1}^{V} j_k(S)} \tag{1}$$

Since the maximum number of link connections formed within the mobile communication network at each time step is $2l$, then $\Sigma_{k=1}^{V} j_k(S) = 2ls$. The analytical solution to the equation was expressed as follows:

$$u_i(S) = \frac{2lS}{V} + z\sqrt{S} \tag{2}$$

When $S = S_0$, the initial activity of node u within the interactive mobile temporal network is $j_u(S_0) = j_u(0)$. The following equation was derived:

$$z = \frac{J_{u0} - 2lS_0/V}{\sqrt{S_0}} \tag{3}$$

Music learning is a process that requires continual reinforcement and review. The forgetting effect refers to the phenomenon where students gradually lose previously acquired knowledge or skills over time. In an interactive mobile learning environment, students deepen their understanding and mastery of musical knowledge through interactions with other learning nodes. However, due to the complexity of learning content and the variability in learning progress, some students may experience knowledge decay during a specific period if timely revision or adequate interaction is lacking. The forgetting effect reduces student activity levels, subsequently diminishing the probability of establishing new learning connections with other nodes. This reduction in interaction frequency can lead to fluctuations in overall group activity levels. Within the temporal network, the forgetting effect is manifested as a decline in node activity, where student engagement progressively decreases over time. In extreme cases, this decline may even result in the severance of connections with other nodes. When calculating the significance of teaching content characteristics, it is necessary to introduce time-exponential decay to describe the process in which numerical values exhibit an exponential decline over time. The following formula was proposed:

$$\frac{dM_u(s)}{ds} = -\beta M_u \tag{4}$$

By solving the differential equation, the following expression was obtained:

$$M_u(s) = M_u(s')e^{-\beta s} \tag{5}$$

This result demonstrates that regardless of the initial value $M_u(s')$, $M_u(s)$ can asymptotically approach zero over the same time interval as long as the exponential decay constant β remains consistent. To incorporate temporal network activity, the time interval of node activation is denoted as π. Let $M_u(s)$ represent the value of M_u at the moment $s_0 + \pi$, and let $M_u(s')$ represent the value of $M_u(s)$ at the moment s_0. That is, the activity level before memory decay can be expressed as $M_u(s') = j_u(s_0)$. The formula was thus updated as follows:

$$M_u(\pi) = j_u(s_0)e^{-\beta\pi} \tag{6}$$

In the evolution of teaching effectiveness in music education, the activity level $M_u(\pi)$ of a node approaches zero if no interaction behavior is observed for the node. To facilitate calculations, it is assumed that the probability of a node being activated within a given time frame in the interactive mobile temporal network follows a uniform distribution. By default, $l/2$ nodes are considered to be activated during each unit time interval, and each node is activated $S/2$ times. The average memory decay duration ($\Delta\pi$) for each node in the interactive mobile temporal network was calculated using the following formula:

$$\Delta\pi = \frac{S}{\frac{S}{2} - 1} = \frac{2S}{S - 2} \tag{7}$$

In an interactive mobile learning environment, student activity is influenced not only by the frequency of interactions with learning content but also by the diversity of learning styles, such as video viewing, practice sessions, discussions, and real-time feedback. Highly active students are typically involved in more interactions, gaining access to a broader range of learning resources, which enhances their understanding of musical knowledge and skills. Conversely, students with low activity levels may experience exacerbated forgetting effects due to insufficient interaction or low revision frequency, potentially hindering their performance in subsequent learning stages. By analyzing the changes in activity levels across student groups, the impact of forgetting effects on teaching effectiveness can be effectively assessed, providing a foundation for optimizing instructional strategies. Figure 2 illustrates the temporal characteristics of an interactive mobile network designed for music education.

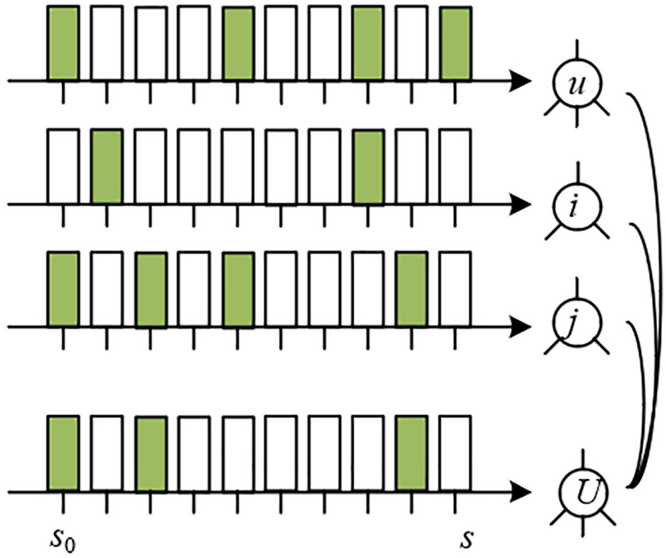

Fig. 2. Temporal characteristics of the interactive mobile network for music education

3 EVOLUTION OF TEACHING EFFECTIVENESS WITH TEMPORAL CHARACTERISTICS IN MUSIC EDUCATION

In the interactive mobile temporal network for music education, the number of node activations reflects different stages or characteristics of teaching effectiveness evolution. This process can be described using a normal distribution function, where the function values are closely associated with the activation levels of nodes during teaching activities and the evolution of teaching stages. By setting distinct expected values (μ) and standard deviations (σ), changes in student engagement and interaction patterns can be analyzed and predicted across various stages of teaching effectiveness evolution. The expected value (μ), as the mean of the normal distribution, determines the trend of node activation over time. When $\mu = 1$, the proportion of activated nodes decreases progressively over time, indicating a decline in student engagement during the later stages of instruction. This trend may suggest either a transition to deeper learning stages or a decline in student interest. Conversely, when $\mu = 0$, the number of activated nodes reaches its peak in the middle of the evolution process, signifying the highest level of student engagement and interaction. This phase typically represents the peak of teaching effectiveness, during which students exhibit maximum investment in teaching activities.

The guiding role of teachers, as opinion leaders in teaching content, is particularly crucial at different stages of teaching effectiveness evolution. During the $\mu = 0$ phase, teaching activities are most active. At this stage, teaching strategies can be adjusted by teachers to sustain and further enhance high levels of student engagement. Interaction design, feedback mechanisms, and motivational strategies implemented during this phase can maximize student enthusiasm, thereby facilitating the deepening of knowledge and skills. In contrast, during the $\mu = 1$ or $\mu = -1$ phases, student activity levels gradually decline. Educators must respond to changes in engagement by adjusting teaching content and methods in a timely manner to prevent instructional activities from becoming stagnant or inefficient. During these stages, the focus of teachers shifts towards reigniting student interest and providing targeted guidance and support to ensure that the learning process is not hindered by a decrease in student participation.

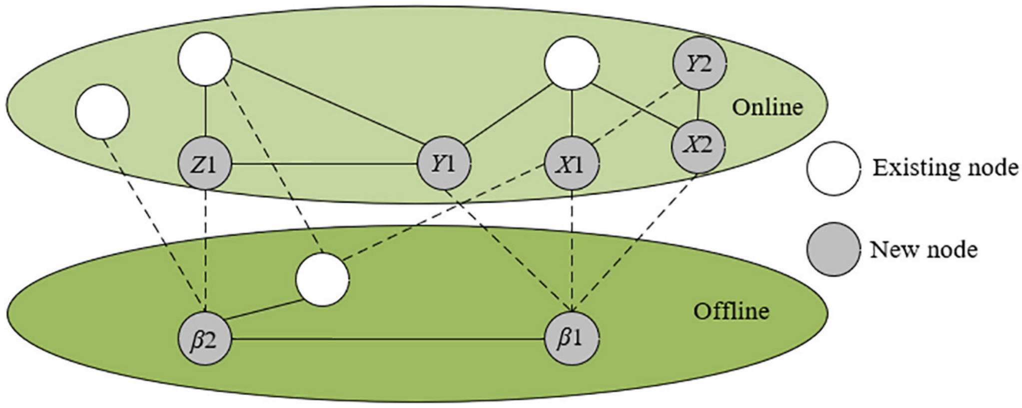

Fig. 3. Collaborative evolution construction of the interactive mobile network considering offline learning individuals

In the model, learning nodes encompass not only offline learning individuals and their corresponding online learning accounts but also the interactions between nodes, particularly the relationship between learning content interactions and node activity levels. Figure 3 illustrates the collaborative evolution construction of an interactive mobile network that considers offline learning individuals. By introducing the concept of neighboring nodes, such as the neighborhood set β_u of node u and the neighborhood set λ_U of offline learning node U, the model captures the propagation and interaction of learning content across different learning individuals and online learning accounts. The activity coefficient of each node determines its influence on other nodes. Highly active nodes exert a greater impact on the collective learning outcomes, making node activity a critical factor in the evolution of teaching effectiveness. Through this mechanism, the interaction of learning content between individuals is influenced not only by their own participation levels but also by the activity levels of their neighboring nodes. This creates a dynamic and temporal process for the evolution of teaching effectiveness.

By incorporating the relationship between node activity and the selection of learning content interaction partners, the study provides a more accurate depiction of learning dynamics among individuals in music education. Each node's learning content is influenced by the activity levels of its neighboring nodes. When selecting interaction partners, nodes compare the activity levels of their neighbors and generate probabilities accordingly to guide the choice of interaction partners. Highly active nodes exert a greater influence on central nodes, and this activity-driven preferential selection mechanism ensures that the dissemination of learning content is not random but rather dominated by highly active nodes. This approach simulates how students in music education select collaborators based on factors such as interests, learning progress, and interaction frequency, thereby forming effective learning content interactions.

For the evolution analysis of teaching effectiveness in music education, the constructed model assists in revealing the evolution of learning content across different stages of student engagement. It also accounts for potential "compromise" phenomena that may arise during the process of learning content selection and interaction among students. For instance, using a mechanism similar to the classical Deffuant model's μ-value, interactions among students are influenced by their individual learning preferences. An increase in the μ-value indicates a greater willingness of students to accept others' perspectives, thereby enhancing the diversity and depth of musical learning. In this model, node activity directly determines the intensity and influence of learning content interactions. By analyzing each student's activity level at each time step and the activity levels of their neighboring nodes, the dynamic changes in teaching effectiveness can be tracked. This analysis reveals how learning preferences and interaction patterns at different stages influence the collective learning process of the group.

Specifically, if a selected node exhibits the highest activity level within its neighborhood, it is assumed to have the greatest influence, as described by:

$$Q_{uk}(s_0) = \frac{j_k(s_0)}{MAX[j_{k\in\beta_u}(s_0)]}\left(or\ Q_{U,K}(s_0) = \frac{j_K(s_0)}{MAX[j_{K\in\lambda_U}(s_0)]}\right) \tag{8}$$

Based on the node activity and the preferential selection mechanism for establishing communication links within the interactive mobile temporal network, the following models were proposed to analyze the evolution of teaching effectiveness in music education:

a) Learning content interaction model for single nodes within the online learning network

$$\begin{cases} P_u(s_0+1) = P_u(s_0) + \frac{1}{2}Q_{uk}(s_0)(P_k(s_0) - P_u(s_0)) \\ P_k(s_0+1) = P_k(s_0) + \frac{1}{2}Q_{ku}(s_0)(P_u(s_0) - P_k(s_0)) \end{cases} \tag{9}$$

b) Learning content interaction model between a single offline node and a single neighboring node in the online learning network

$$\begin{cases} P_U(s_0+1) = P_U(s_0) + \frac{1}{2}Q_{UK}(s_0)(P_K(s_0) - P_U(s_0)) \\ P_K(s_0+1) = P_K(s_0) + \frac{1}{2}Q_{KU}(s_0)(P_U(s_0) - P_K(s_0)) \end{cases} \tag{10}$$

For scenarios involving single-to-multiple node interactions in learning content, node activity was assigned as a weight in this study. The corresponding model equations were defined as follows:

a) Learning content interaction model for a single node and multiple neighboring nodes in the online learning network

$$P_u(s_0+1) = P_u(s_0) + \frac{1}{2}\left(\left(\frac{\sum_{K\in\beta_u} j_k(s_0)P_k(s_0)}{\sum_{k\in\beta_u} j_k(s_0)}\right) - P_u(s_0)\right) \tag{11}$$

b) Learning content interaction model for a single offline node and multiple neighboring nodes in the online learning network

$$P_U(s_0+1) = P_U(s_0) + \frac{1}{2}\left(\left(\frac{\sum_{K\in\lambda_U} j_K(s_0)P_K(s_0)}{\sum_{K\in\lambda_U} j_k(s_0)}\right) - P_U(s_0)\right) \tag{12}$$

Furthermore, the activity levels of nodes within the interactive mobile temporal network exert a greater influence on offline nodes as their activity increases. This relationship can be expressed as follows:

$$P_U(s_0+1) = P_U(s_0) + \frac{1}{2}\left(\left(\frac{\sum_{u \in J_U} j_u(s_0) P_u(s_0)}{\sum_{u \in J_U} j_u(s_0)}\right) - P_U(s_0)\right) \tag{13}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Three experiments were conducted in this study. Experiment 1 examined the impact of variations in the number of opinion leaders within teaching content on the learning effectiveness and activity levels of the student group. The results, as illustrated in Figure 4, indicate that as the number of opinion leaders increases, the learning effectiveness of the student group progressively approaches the target value. Over time, the effectiveness converges, and the gap between the average learning effectiveness of online and offline student groups narrows. This trend suggests that an increase in opinion leaders can, to some extent, improve the learning effectiveness of student groups, particularly in blended teaching models that integrate online and offline approaches, where learning effectiveness tends to align. However, it is noteworthy that the marginal improvement in learning effectiveness diminishes as the number of opinion leaders increases. This indicates that the influence of opinion leaders may reach a saturation point, beyond which further increases in their number contribute minimally to enhancing learning effectiveness. This phenomenon reflects real-world educational environments, where blended teaching models effectively narrow the gap in learning effectiveness under certain conditions, thereby promoting educational equity. The results also reveal that the activity levels of student groups are unaffected by the number of opinion leaders in the teaching content. This can be attributed to the evolutionary processes in music education, particularly within interactive mobile networks, where students' impressions of the activity levels of other group members gradually fade, leading to stable activity levels. In other words, while the number of opinion leaders has a significant impact on learning effectiveness, it does not noticeably influence student activity levels. Related findings from the experiment indicate that the activity levels of online student groups are significantly higher than those of offline groups. This is consistent with the characteristics of online learning environments, which are often marked by high interactivity and rapid information transmission. Consequently, although opinion leaders can improve learning effectiveness to a certain extent, student activity levels remain constrained by other factors, such as individual learning habits and platform design. This finding underscores the complexity of considering multiple factors comprehensively in the education system.

Experiment 2 investigated the influence of changes in teaching content on the learning effectiveness and activity levels of student groups in music education. The results, as presented in Figure 5, indicate that larger expected values correspond to earlier stages of music education evolution. During the evolution of learning effectiveness, the earlier the introduction of opinion leaders within teaching content, the more likely the student group is to achieve the target learning effectiveness. Particularly in the early stages of educational evolution, the guiding effect of opinion leaders in teaching content is pronounced, suggesting that opinion leaders do not necessarily need to be introduced at the outset but can be progressively integrated based on the actual learning process. The critical approach involves "early detection and early guidance." This phenomenon reveals that in music education, sufficient time is available for teaching platforms to implement effective guidance, ensuring that student groups continuously optimize their learning effectiveness throughout the educational process, ultimately achieving optimal results. Furthermore, the experiment observed differing trends in the average activity levels of online and offline student groups as music education evolution progressed. With increasing expected values, the activity levels of both online and offline groups gradually increased, with the magnitude of change being greater in online groups. This result highlights the advantage of interactive mobile networks in enhancing student activity levels compared to traditional offline education. In the early stages of music education evolution, with the gradual introduction of teaching content and the increase in the number of individual participants, student groups exhibited higher activity levels, which stabilized or even declined in later stages. This outcome reflects the influence of overall educational atmosphere and individual interactions on student activity as the number of participants increases. The higher interactivity and engagement of online platforms particularly contributed to elevated activity levels. To sustain activity levels and guide student groups towards improved learning effectiveness, educational platforms must dynamically adjust their strategies at different stages of education evolution.

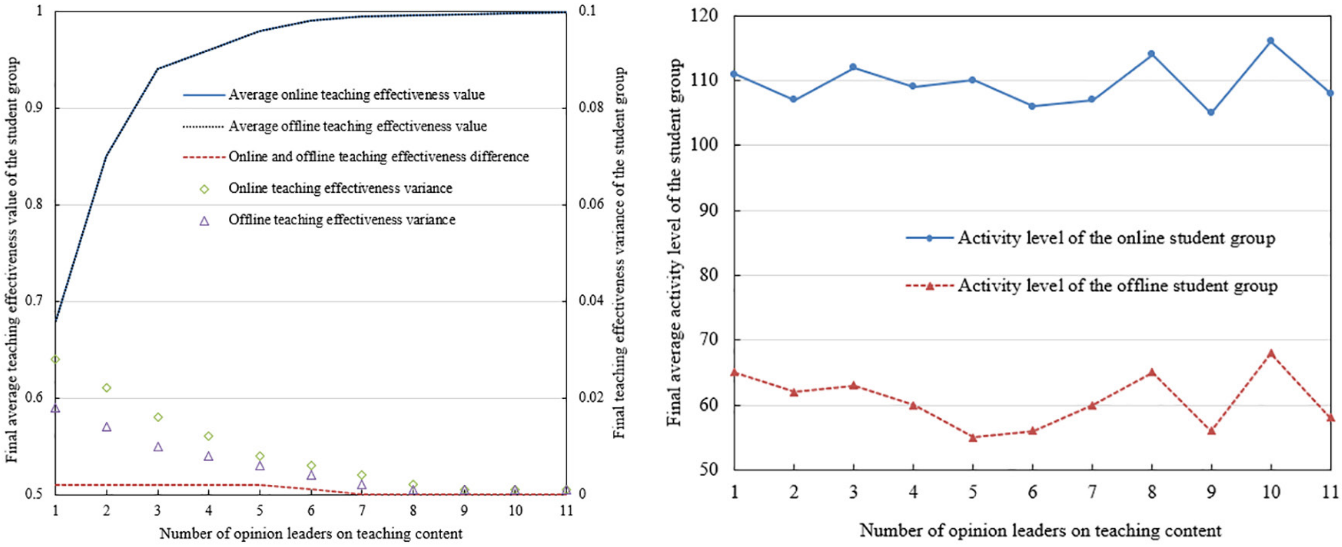

Fig. 4. Final average teaching effectiveness value, variance, and average activity level of the student group in the first experiment

Experiment 3 explored the impact of variations in the activity levels of opinion leaders within teaching content on the learning effectiveness and activity levels of student groups. The results presented in Figure 6 indicate that, although the initial activity levels of opinion leaders increased, this change did not significantly affect the learning effectiveness or activity levels of the student group. This phenomenon can be attributed to the forgetting effect within student groups. Over time, students gradually forget past interactions and experiences, weakening the influence of the initial activity levels of opinion leaders on subsequent learning processes. This observation suggests that student group activity is not entirely dependent on initial conditions but is more influenced by the educational evolution stage. As the learning stages progress during music education, student activity levels tend to stabilize, reflecting the group's adaptation to and engagement with the current learning environment. Furthermore, the findings highlight a strong correlation between student activity levels and the current stage of educational evolution. These stages reflect the platform's emphasis on teaching content, where adjustments and optimizations in content at different time periods directly influence student activity levels. Specifically, during different stages of education evolution, the platform can adjust teaching content, guide student interactions, and refine feedback mechanisms to influence activity levels to some extent. When the platform places greater focus on teaching content, an increase in student activity levels is observed. Conversely, reduced focus on teaching content leads to a decline in activity levels. This finding underscores the critical role of teaching content design and platform strategy adjustments in shaping student activity levels. Educational platforms must dynamically adjust content and strategies based on feedback from student groups and the needs of the educational process, thereby maximizing student interest and participation.

Table 1. Correlation analysis between interaction behavior patterns and teaching effectiveness of different student groups

Interaction Behavior Pattern Number	Central Node		Teaching Activity Organizer		Teaching Content Guide		Other Nodes	
	R	R^2	*R*	R^2	*R*	R^2	*R*	R^2
1	0.425*	0.157	0.469*	0.211	0.358*	0.122	0.356*	0.124
2	0.478*	0.235	0.225*	0.053	0.278*	0.083	0.315	0.114
3	0.235*	0.048	0.236*	0.047	0.135	0.015	0.278	0.081
4	0.365*	0.135	0.312*	0.112	0.369*	0.134	0.269*	0.082
5	0.436*	0.178	0.425*	0.198	0.245*	0.048	0.135	0.016
6	0.287*	0.076	0.268*	0.077	0.236*	0.044	0.178	0.034
7	0.379*	0.135	0.179	0.032	0.368	0.067	0.252	0.044
8	0.298*	0.083	0.289*	0.087	0.236	0.064	0.113	0.012

Note: *means $P < 0.05$.

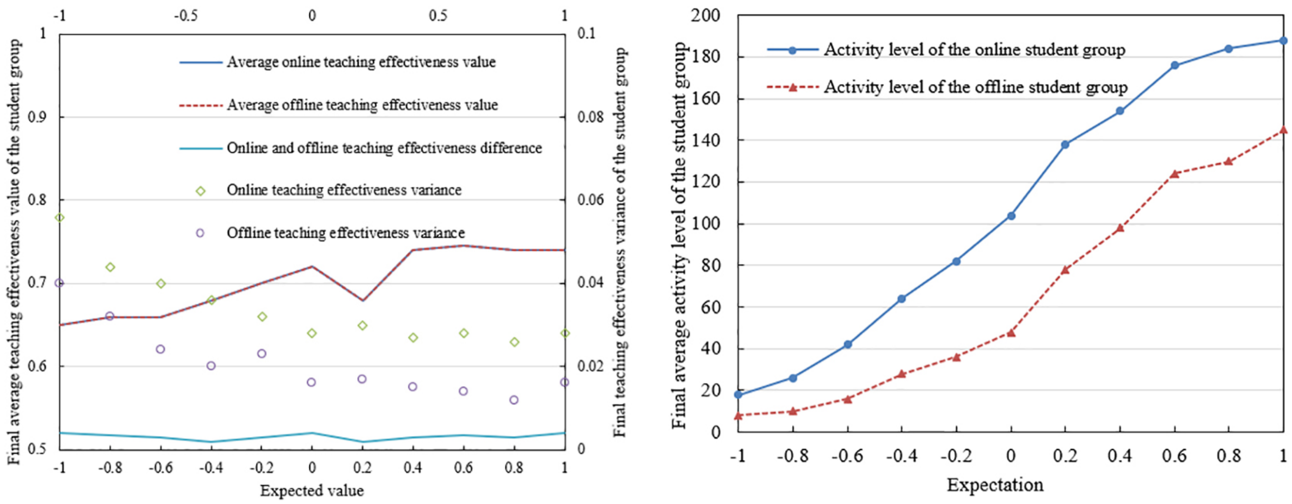

Fig. 5. Final average teaching effectiveness value, variance, and average activity level of the student group in the second experiment

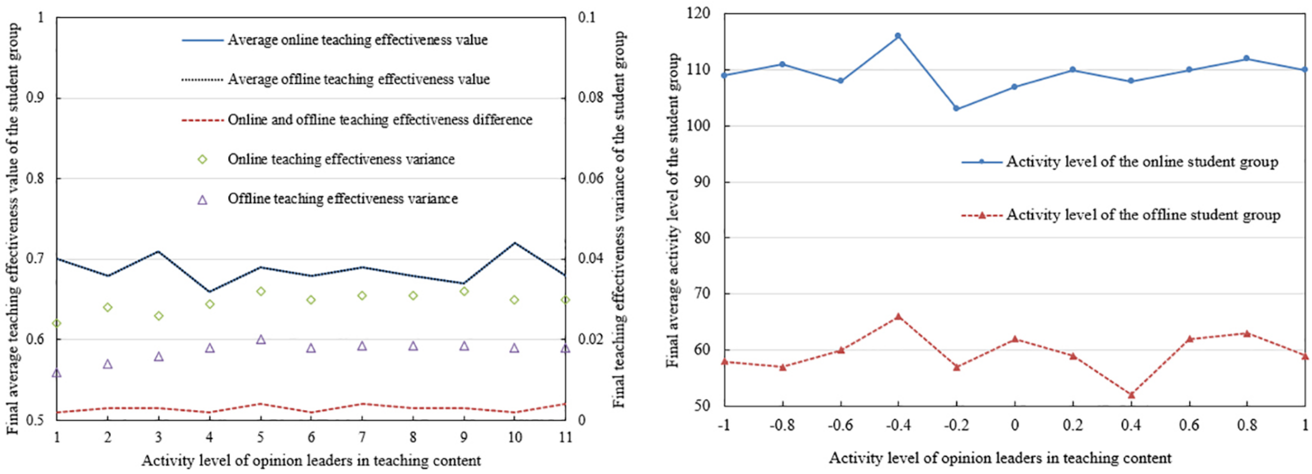

Fig. 6. Final average teaching effectiveness value, variance, and average activity level of the student group in the third experiment

Table 1 further explores the correlation between different interaction behavior patterns and teaching effectiveness. The values of R and R^2 in the table reflect the strength and explanatory power of each interaction behavior pattern on teaching effectiveness. Based on the experimental data, Interaction Behavior Pattern 1 (online single-to-online single interaction) exhibits significant positive correlations across multiple dimensions (e.g., R = 0.425*, 0.469*, 0.358*, etc.). The roles of teaching activity organizers and teaching content guides are particularly prominent, indicating that this pattern effectively promotes learning effectiveness in student groups. In Interaction Behavior Pattern 2 (offline single-to-online multiple interaction), although the overall correlation is weaker (R = 0.225*, 0.278*, etc.), a positive influence is still observed. The correlation is particularly evident in the relationship between teaching content guides and other nodes. While the influence is weaker, statistical significance is maintained. For Interaction Behavior Patterns 3 and 4, correlations are considerably lower. In particular, Pattern 3 (offline single-to-online multiple interaction) shows R^2 values close to zero in most cases (e.g., R^2 = 0.015), indicating a limited impact on student learning effectiveness. Patterns 5 to 8, which involve combinations of multiple interaction modes, display consistent positive correlations. Pattern 5 (a combination of Patterns 1, 2, and 3) demonstrates the strongest correlations across all dimensions (e.g., R = 0.436*, 0.425*, etc.). These finding highlights that combining multiple interaction behaviors can significantly enhance teaching effectiveness.

The analysis indicates that online interaction patterns (e.g., Pattern 1) within the interactive mobile network exhibit a stronger relationship with teaching effectiveness. The roles of teaching activity organizers and teaching content guides are particularly effective in improving learning effectiveness. The influence of teaching content guides is especially pronounced, suggesting that precise online teaching design and personalized guidance can maximize student learning effectiveness. In contrast, the impact of offline interaction patterns on learning effectiveness is relatively weaker. Purely offline interactions have limited effectiveness in improving learning effectiveness, particularly when compared to online interactions. The roles of offline interactions in content guidance and activity organization are less influential. However, combining different interaction patterns (e.g., Patterns 5 or 6) can effectively address the limitations of single-mode interactions. The diversification of online and offline interaction combinations enhances teaching effectiveness and student group activity levels, creating a more efficient and interactive learning environment. Therefore, teaching platforms should emphasize the organic integration of online and offline interaction patterns and optimize teaching design and student interaction mechanisms, thereby promoting comprehensive development across multiple dimensions within student groups.

5 CONCLUSION

This study provides an in-depth exploration of the application of interactive mobile technology in music education, offering a comprehensive analysis of how different network characteristics improve learning experiences and enhance the learning effectiveness and activity levels of student groups. Particular attention is given to the impact of teaching content and the guiding role of opinion leaders on the dynamic evolution of learning effectiveness of student groups within a temporal context. Through a series of experiments, the significant influence of changes in teaching content and the activity levels of opinion leaders on student group learning effectiveness was revealed. The experimental results demonstrate that the early introduction of opinion leaders within teaching content contributes to better achievement of learning effectiveness in student groups. Additionally, varying trends in the impact of online and offline interaction patterns on student activity levels were observed at different stages of educational evolution. Online interaction patterns were found to be more effective than offline patterns in enhancing student activity levels. Furthermore, the correlation between different interaction behavior patterns and teaching effectiveness was analyzed. It was found that diverse combinations of interaction patterns, especially the integration of online and offline modes, effectively improved both the overall learning effectiveness and activity levels of student groups.

Overall, the findings of this study possess significant theoretical and practical implications, particularly in offering novel perspectives for the design of interactive mobile technologies and educational platforms. The quantitative analysis of the effects of various teaching strategies and interaction patterns provides a foundation for the design and optimization of future educational platforms, highlighting the importance of interactivity and personalized design. Nevertheless, some limitations exist. Firstly, the study focused predominantly on the domain of music education, and different disciplines may exhibit varying effects. Secondly, the experimental samples and contexts were relatively limited. Future studies could extend the scope to broader educational settings and more complex interaction patterns to validate the generalizability and applicability of the conclusions. Future research directions could include further exploration of the application of interactive mobile technologies across different disciplines. Special emphasis could be placed on how emerging technologies such as artificial intelligence and big data analytics can facilitate greater personalization and optimization of the educational experience, as well as how teaching content and interaction patterns can be dynamically adjusted according to different educational stages and dynamic learner characteristics.

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