Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 19 No. 2 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijim.v19i02.53747

PAPER

# The Impact of Mobile Technology on English Writing Teaching: The Relationship between Interactive Feedback and Autonomous Learning Abilities

**Weifeng Deng,**
**Lin Wang(✉)**

Hainan Vocational University of Science and Technology, Haikou, China

wanglintaichi@163.com

**ABSTRACT**

With the rapid development of information technology (IT), mobile technology has been widely applied in the field of education, particularly in language learning. English writing, as one of the core skills in language acquisition, faces numerous challenges within traditional teaching models, such as limited learner autonomy and the difficulty of meeting individualized needs. In recent years, mobile technology-assisted English writing teaching has become a new research focus, with interactive feedback mechanisms and the enhancement of autonomous learning abilities being identified as key factors influencing instructional effectiveness. This study aims to explore mobile network-based English writing teaching, specifically analyzing how location-aware features and interactive feedback can enhance students' autonomous learning abilities. In particular, the study investigates the forms and challenges of mobile network-assisted English writing teaching, examining mobile network discovery technologies, similarity calculation, and evolutionary computation methods relevant to English writing teaching, and proposes strategies for enhancing autonomous learning through interactive feedback.

**KEYWORDS**

mobile technology, English writing teaching, interactive feedback, autonomous learning abilities, mobile network, similarity calculation, evolutionary computation

## 1 INTRODUCTION

With the rapid development of information technology (IT), the application of mobile technology in the field of education has become increasingly widespread, particularly demonstrating significant potential in English writing teaching [1–5]. Traditional English writing teaching methods are often characterized by delayed feedback, fragmented learning resources, and insufficient student autonomy in learning [6, 7]. The introduction of mobile technology provides a new avenue for addressing these issues. In particular, mobile networks, as a location-based dynamic

Deng, W., Wang, L. (2025). The Impact of Mobile Technology on English Writing Teaching: The Relationship between Interactive Feedback and Autonomous Learning Abilities. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(2), pp. 180–194. https://doi.org/10.3991/ijim.v19i02.53747

Article submitted 2024-07-23. Revision uploaded 2024-11-10. Final acceptance 2024-11-11.

technological platform, not only offer the flexibility of learning support anytime and anywhere but also facilitate the enhancement of students' English writing abilities through real-time interactive feedback [8–11]. Therefore, exploring effective integration strategies for mobile network technology in English writing teaching and analyzing its impact on students' autonomous learning abilities holds significant research value.

The significance of this study lies in addressing the gap in current research regarding the relationship between mobile technology-assisted English writing teaching and the development of students' autonomous learning abilities. The innovative application of mobile technology, particularly mobile networks, can offer personalized and flexible learning experiences in English writing teaching. Through interactive feedback, students can receive timely suggestions and guidance from teachers or peers during the writing process, which not only enhances writing abilities but also strengthens students' awareness of autonomous learning and boosts their self-confidence. Investigating how these interactive feedback mechanisms contribute to the improvement of students' autonomous learning abilities can provide theoretical foundations for English language teaching practice while also offering new perspectives for the development of educational technologies.

Although previous studies have explored the impact of mobile technology on English writing teaching, many of these studies exhibit certain limitations [12–15]. First, existing research tends to focus on the use of mobile applications and the enhancement of writing skills, with insufficient in-depth investigation into the relationship between interactive feedback mechanisms during the writing process and the development of students' autonomous learning abilities [16, 17]. Second, research on how mobile network technologies, particularly location-based dynamic networks, can be utilized to optimize feedback mechanisms and personalize learning paths remains relatively underdeveloped. Furthermore, most studies concentrate on individual teaching tools or applications, often overlooking the synergistic effects between different tools and the long-term influence of network evolution.

The main focus of this study is organized into four parts. First, the specific applications of mobile networks in English writing teaching were detailed, along with an exploration of the practical issues and challenges they face. Second, a study of the characteristics of mobile networks tailored to assist English writing teaching was conducted, examining both their advantages and limitations, followed by corresponding improvement strategies. Third, the application of mobile network similarity calculation and evolutionary computing in writing instruction was explored, particularly in terms of how network evolution and data computation can optimize teaching feedback. Finally, strategies for enhancing autonomous learning abilities through mobile network interactive feedback were proposed, exploring how technological means can be leveraged to strengthen students' motivation for autonomous learning and offering concrete teaching design ideas for educators. The findings of this study are expected not only to provide new methodological support for English writing teaching but also to contribute to the innovative application of educational technologies and the transformation and upgrading of teaching models.

## 2 SPECIFIC FORMS AND PROBLEM DESCRIPTIONS OF MOBILE NETWORK-ASSISTED ENGLISH WRITING TEACHING

Mobile technology-assisted English writing teaching can be implemented through the design of geotagged writing tasks. Teachers may assign writing assignments related to specific locations, such as requesting students to write an article about famous landmarks in their city or to describe their daily commuting routes and the scenery along the way. This approach not only stimulates students' interest in writing but also enables them to find inspiration and material for writing from their everyday lives. Furthermore, the reminder functions based on Global Positioning System (GPS) can play a significant role. When students approach a location relevant to their writing task, mobile devices can automatically send reminders, prompting them to gather and record relevant material. This immediate reminder system ensures timely collection of materials while allowing students to brainstorm their writing ideas in real-world contexts, thus enhancing the authenticity and practicality of the writing process. Students may also share their current location via mobile networks and collaborate with classmates to complete writing tasks. For example, a group of students can collect materials from different locations and then consolidate and collaborate on writing through an online platform. Mobile networks further enable students to instantly access data related to the writing topic. For instance, when writing about urban traffic, students can use real-time traffic data to support their arguments, thereby making their writing more convincing and grounded in reality. Additionally, students may conduct surveys and collect data via mobile devices, such as performing street interviews and incorporating the results into their writing. This approach not only enhances the authenticity of the work but also develops students' data analysis skills and critical thinking.

Mobile network-assisted English writing teaching, with a focus on location-based networks, was explored in this study. The interaction feedback network in English writing teaching is represented using the standard graph notation from graph theory, denoted as $H = (N.R)$, where $N$ denotes the set of all participants in the English writing teaching process, including students and teachers, and $R$ represents the interactive relationships between these users via the mobile network. Each node $n_u \in N_v$ represents a student or teacher, and each edge $r_{uk} \in R_v$ represents an interaction between a student and a teacher or between students. The weight $q_{uk}$ of an edge indicates the frequency or intensity of the interaction. The network was modeled using snapshot graphs, which capture how the interactions between students and teachers evolve over time, particularly how a dynamic teaching support network is formed within the mobile network. A time granularity parameter was used to refine the periods of teaching interaction feedback, allowing for a more precise capture of the students' learning states and interaction intensities within a specific time frame, which, in turn, enables the analysis of how timely feedback can enhance students' autonomous learning abilities.

## 3 MOBILE NETWORK DISCOVERY FOR SUPPORTING ENGLISH WRITING TEACHING

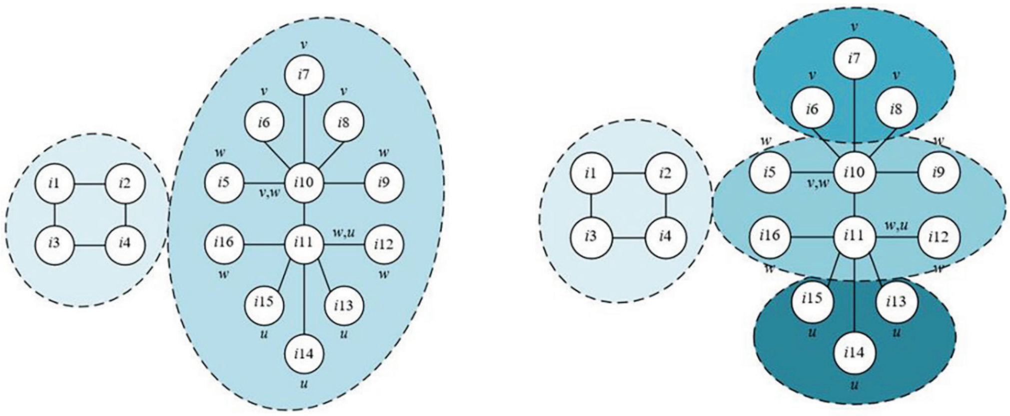
As for the evolutionary framework for location-based mobile network structures designed to support English writing teaching, a time model of the interactive mobile network was first constructed through time-slice partitioning. In this process, each user within the mobile network formed a dynamic interaction network within a specified time range using geographical location data, learning activity data, and interactive feedback data. After obtaining the static interactive mobile network based on time-slice partitioning, the framework applied static network analysis methods to calculate the data for each time slice in detail. By calculating the interaction intensity between each node and the other nodes, the learning progress, feedback quality, and changes in autonomous learning abilities of learners during each time period can be assessed. Furthermore, location-based analysis can further explore the differences in students' learning behaviors across various geographical environments. Finally, by integrating the results from the static network analysis, a mobile network structure evolution model was constructed to analyze how the interaction feedback and learning behavior of students evolve over time throughout the learning process, thereby providing strategies and recommendations for enhancing students' autonomous learning abilities.

### 3.1 Time model

To accurately capture the learning dynamics of students within each time period and to adjust teaching methods and interactive feedback strategies accordingly, a mobile network time model for supporting English writing teaching was first constructed. This model aims to capture students' writing behaviors and interaction feedback across different time periods by precisely dividing time segments. Initially, based on the set time granularity, students' interaction data were evenly partitioned into multiple subsets, each representing a static interactive mobile network. The mobile network for each time period formed an independent "snapshot," recording the interaction frequency and relationships between all users during that period. The evolution of the entire interactive mobile network structure can be represented as a set of consecutive subsets along a timeline, $\{H_1, H_2, \ldots, H_v\}$. By performing mobile network discovery on $H_v$, the mobile network set under the current writing task can be obtained, denoted as $H_v = \{H_{1v}, H_{2v}, \ldots, H_{lv}\}$.

### 3.2 Location-based mobile network discovery

Figure 1 illustrates two different methods for mobile network discovery. The mobile network discovery algorithm employed in this study is based on the analysis of interactions and location information between teachers and students, aimed at enhancing teaching effectiveness and improving students' autonomous learning abilities. The process consists of four specific steps:




a) Based on structure b) Based on location

**Fig. 1.** Methods of mobile network discovery

Step 1: Assigning weights to edges based on interactive mobile network users' check-in data: In this stage, the algorithm constructed a location-based weight function by collecting check-in data from interactive mobile network users at specific locations. Specifically, the weight $d(r_{uk})$ of the interaction edge $r_{uk}$ between two interactive mobile network users $i_u$ and $i_k$ was assigned based on the frequency of their check-ins and interactions at the same location. The weight reflects the intensity of interaction between the two users at a specific time and location. For example, if two users (a teacher and a student) interact multiple times at the same time and location, the weight of the edge will be higher, indicating a stronger interaction. Conversely, if the interaction is infrequent, the edge weight will be lower. The following binary weight function was proposed to define the interaction relationship between $i_u$ and $i_k$:

$$d_y(r_{uk}) = \begin{cases} 1; IF\left|L_u \cap L_k\right| > 0 \\ 0; IF\left|L_u \cap L_k\right| \leq 0 \end{cases} \tag{1}$$

The weight function, as shown in Equation (2), reflects the diversity of the interaction locations between the teacher and student based on the total number of common check-in locations shared by $i_u$ and $i_k$.

$$d_o(r_{uk}) = \left|L_u \cap L_k\right| \tag{2}$$

The check-in weight function was defined as the lower value of the check-in frequency between $i_u$ and $i_k$ at all shared locations, and the expression is:

$$d_z(r_{uk}) = \sum_{l_o \in (L_u \cap Lk)} MIN(z_{uo}, z_{ko}) \tag{3}$$

A ratio-based weight function was defined as the maximum value of the ratio of the number of check-ins by $i_u$ and $i_k$ at all shared locations to the total number of check-ins at those locations. Let the total number of check-ins by users in $N$ at location $l_o$ be represented by $Z_o$, and the expression is:

$$d_e(r_{uk}) = \underset{l_o \in (L_u \cap L_k)}{MAX}\left(\frac{Z_o}{\left|I_o\right|}\right) \tag{4}$$

Step 2: Removal of low-weight edges: To improve the accuracy and efficiency of the algorithm, low-weight edges, which are below a preset threshold *ft*, were removed from the interactive mobile network graph in this step. The purpose of this operation is to eliminate those interactions that have minimal frequency or contribution to learning feedback.

Step 3: Removal of isolated nodes: In English writing teaching, isolated nodes typically represent users who have not participated in any interactions. These users may have been inactive during a particular time period, or their interaction frequency with others may be too low. To ensure the effectiveness of the teaching network, the removal of isolated nodes eliminates unnecessary noise from the network analysis and reduces computational complexity.

Step 4: Application of the standard mobile network discovery algorithm for network discovery: After the preceding steps, the remaining mobile network structure can be analyzed using a standard mobile network discovery algorithm. By analyzing the structure of the mobile network, educators can identify students who are experiencing interaction isolation or lack of feedback during the writing process, enabling timely and personalized teaching interventions. The algorithm employed in this study is the Louvain detection algorithm, which optimizes the modularity of the interaction relationship graph. Let the modularity be denoted by $W$, the total number of edges in the interaction relationship graph by $l$, the weight between nodes $u$ and $k$ by $X_{uk}$, and the sum of the weights pointing to nodes $u$ and $k$ by $j_u$ and $j_k$, respectively. The modularity calculation method is expressed as follows:

$$W = \frac{1}{2l} * \sum_{uk} \left[ X_{u,k} - \frac{j_u * j_k}{2m} l \right] * \sigma(Z_u, Z_k) \tag{5}$$

## 4 MOBILE NETWORK SIMILARITY AND EVOLUTION CALCULATION FOR ASSISTED ENGLISH WRITING TEACHING

### 4.1 Similarity calculation

Similarity calculation is a key step in evaluating the evolution of mobile networks. The location-based mobile networks for English writing teaching may exhibit different member compositions and interaction patterns across different time periods. Therefore, similarity calculation is required to assess the degree of network evolution between these time periods. Specifically, the similarity between two time periods' mobile networks is calculated based on the proportion of common members in the two networks. If the proportion of shared members between the two time periods exceeds a set similarity threshold, the two networks are considered similar. The setting of this threshold is closely related to the stability of the network. In the context of interactive English writing teaching, the interaction between teachers and students is often influenced by various factors, such as class schedules, student engagement, and learning tasks. For more stable learning environments, such as writing groups or classrooms held at fixed times, the network members remain relatively constant, and the interaction relationships between students are more fixed. As such, a higher similarity threshold can be set to ensure effective tracking of stable and continuous interaction relationships within the teaching process. Let the $u$-th and $k$-th mobile sub-networks in the consecutive time periods $s$ and $s + 1$ be represented by $Z_{us}$ and $Z_{k(s+1)}$, respectively, as shown in the equation:

$$SIM\left(Z_{us}, Z_{k(s+1)}\right) = MIN\left( \frac{\left|Z_{us} \cap Z_{k(s+1)}\right|}{Z_{us}}, \frac{\left|Z_{us} \cap Z_{k(s+1)}\right|}{Z_{k(s+1)}} \right) \geq \varphi \tag{6}$$

If the number of common members in the mobile networks $C_{it}Z_{us}$ and $C_{j(t+1)}Z_{k(s+1)}$ and their proportion relative to the total number of members in the networks exceeds the similarity threshold $\theta\varphi$, the two mobile networks are considered similar.

### 4.2 Evolution calculation

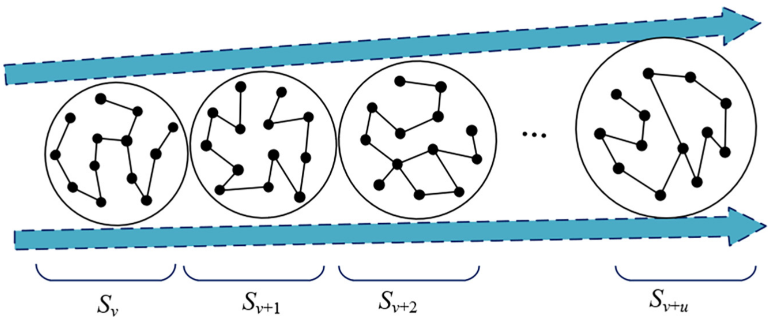



**Fig. 2.** Illustration of mobile network evolution

In the location-based mobile networks for assisted English writing teaching, network evolution is a dynamic process. Over time, the interaction relationships and feedback mechanisms between teachers and students continually change. This process can be represented by a series of snapshot graphs at different time intervals, denoted as $<H_1, H_2, \ldots, H_v>$. Figure 2 provides an illustration of mobile network evolution. As time progresses, students' locations and interaction behaviors continually change, influencing their roles and positions within the mobile network. In this evolutionary process, six major mobile network events play key roles:

**a)** Growth event: This occurs when new learning tasks or interaction opportunities are introduced, leading to the addition of new students and teachers to the network, which results in an increase in the number of network nodes.
**b)** Sustained event: This refers to certain interaction relationships within the network remaining stable over a period of time. The interaction patterns between students and teachers do not change significantly, reflecting the continuity of the teaching activities.
**c)** Reduction event: This occurs when the interaction frequency of some students declines, possibly due to a lack of feedback or a decrease in learning interest, causing these students to "withdraw" from the network.
**d)** Splitting event: This is characterized by a change in the interaction patterns of student groups. Some students form new groups or discussion groups during a particular time period, causing the original learning network to be split into multiple sub-networks.
**e)** Merging event: This happens when different groups or learning communities interact and collaborate, merging into a more cohesive network, thereby promoting cooperative learning among students.
**f)** Disappearance event: This reflects the absence of effective interaction from certain learners over an extended period, ultimately leading to their complete disappearance from the network.

Figure 3 provides examples of the six mobile network evolution events.

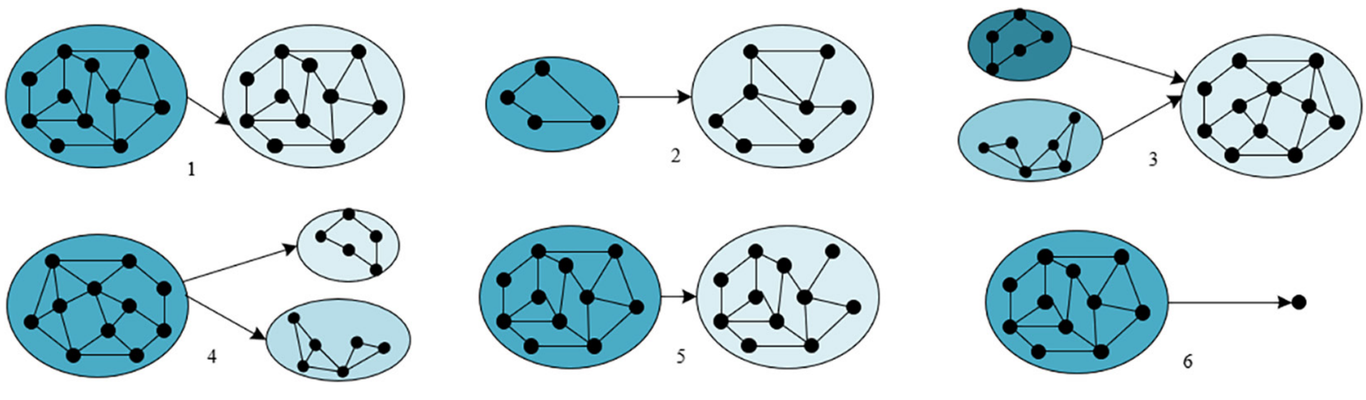



**Fig. 3.** Examples of mobile network evolution events

In order to accurately identify and analyze the evolution of teacher-student interaction feedback across different time periods, two key parameters were introduced in the mobile network evolution calculation: similarity threshold ($\varphi$) and fluctuation threshold ($\theta$). The similarity threshold ($\varphi$) was used to measure the member similarity between mobile networks across different time periods. Specifically, if the similarity between the mobile network $Z_{us}$ in one time period and the mobile network $Z_{k(s+1)}$ in the subsequent time period exceeds the threshold $\varphi$, these two networks are considered to be similar during the evolution process and may belong to the same group or event. By setting a similarity threshold, network structure changes such as splitting and merging can be effectively identified. The fluctuation threshold ($\theta$) was used to measure the extent of changes in the number of members within a mobile network across different time periods. It reflects the percentage of increase or decrease in the number of members relative to the total size of the mobile network. In the context of interactive feedback for English writing teaching, the fluctuation threshold helps to analyze changes in student participation during a given teaching phase, thus determining whether the network is in a growth, sustained, or reduction state. Given a mobile network $Z_{us}$ in the time period $s$ and a subsequent evolving mobile network $Z_{k(s+1)}$ in the time period $s+1$, the number of members in the two networks is denoted as $v_u^s$ and $v_k^{s+1}$, respectively. The definition of fluctuation is as follows:

$$FLU\left(Z_{us}, Z_{k(s+1)}\right) = \frac{v_k^{s+1}}{v_k^s} - 1 \tag{7}$$

By combining the similarity threshold ($\varphi$) and fluctuation threshold ($\theta$), events can be appropriately tagged to the mobile network, enabling effective identification of various evolutionary events. The calculation principles for these events are explained as follows:

If the similarity between the mobile networks $Z_{k(s+1)}$ and $Z_{us}$ exceeds $\varphi$, and the fluctuation threshold lies between $-\theta$ and $\theta$, this is considered a sustained event, as expressed by:

$$SIM\left(Z_{us}, Z_{k(s+1)}\right) \geq \varphi \wedge -\theta \leq FLU\left(Z_{us}, Z_{k(s+1)}\right) \leq \theta \tag{8}$$

If the similarity between the mobile networks $Z_{k(s+1)}$ and $Z_{us}$ exceeds $\varphi$, and the fluctuation threshold lies between $-\theta$ and $\theta$, this is also considered a sustained event, as expressed by:

$$SIM\left(Z_{us}, Z_{k(s+1)}\right) \geq \varphi \wedge FLU\left(Z_{us}, Z_{k(s+1)}\right) > \theta \tag{9}$$

If the similarity between the mobile networks $Z_{k(s+1)}$ and $Z_{us}$ exceeds $\varphi$, and the fluctuation threshold is less than $-\theta$, this is considered a reduction event, as expressed by:

$$SIM\left(Z_{us}, Z_{k(s+1)}\right) \geq \varphi \wedge FLU\left(Z_{us}, Z_{k(s+1)}\right) < -\theta \tag{10}$$

Let the set of mobile networks in the time period $s + 1$ be denoted as $Z_{*(s+1)} = \{Z_{1(s+1)}, \ldots, Z_{k(s+1)}\}$. If the similarity threshold between $Z_{us}$ and two or more mobile networks within $Z_{*(s+1)}$ exceeds $\varphi$, it is considered that a splitting event has occurred in the mobile network across consecutive time periods, as expressed by:

$$\forall Z_{k(s+1)} \in Z_{*(s+1)}, SIM\left(Z_{us}, Z_{k(s+1)}\right) \geq \varphi \wedge SIM\left(Z_{us}, \cup\left\{Z_{*s}\right\}\right) \geq \varphi \tag{11}$$

If the similarity threshold between every mobile network in the set $Z_{*s} = \{Z_{1s}, \ldots, Z_{ks}\}$ from time period $s$ and the mobile network $Z_{k(s+1)}$ exceeds $\varphi$, it is considered that a merging event has occurred in the mobile network, as expressed by:

$$\forall Z_{us} \in Z_{*s}, SIM\left(Z_{us}, Z_{ks(t+1)}\right) \geq \varphi \wedge SIM\left(\cup\left\{Z_{*s}\right\}, Z_{k(s+1)}\right) \geq \varphi \tag{12}$$

If no mobile network $Z_{k(s+1)}$ has a similarity threshold greater than $\varphi$ with $Z_{us}$, it is considered that a disappearance event has occurred in the mobile network, as expressed by:

$$SIM\left(Z_{us}, Z_{k(s+1)}\right) < \varphi \tag{13}$$

## 5 STRATEGIES FOR ENHANCING AUTONOMOUS LEARNING ABILITIES BASED ON MOBILE NETWORK INTERACTIVE FEEDBACK

Based on the analysis of the evolution of location-based mobile network structures and combined with the interactive feedback mechanism, a comprehensive and scientific solution for enhancing students' autonomous learning abilities can be provided.

**a)** Promoting student interaction and collaborative learning: If the analysis reveals limited interaction between students and their peers, it may indicate a lack of opportunities or motivation for collaborative learning. Consequently, teachers can foster interaction and knowledge sharing between students by designing group discussions, collaborative projects, and similar activities, thereby enhancing their learning motivation and teamwork awareness.

**b)** Personalized feedback and support: By analyzing the interaction patterns between students and teachers during the learning process, teachers can identify students who may require additional support. For students with slower progress or learning difficulties, personalized feedback and guidance can be provided based on their learning behaviors, helping them overcome learning bottlenecks and stimulating their interest in learning and autonomous learning capabilities.

**c)** Dynamic adjustment of learning resources: By analyzing students' interactions with learning resources, their preferences and needs for different types of learning materials can be understood. If certain students frequently engage with videos, interactive textbooks, or online quizzes during their learning process, while others prefer traditional textual resources, teachers and educational platforms can dynamically recommend learning materials that suit the students' needs. This tailored approach help students select appropriate learning resources at different stages, thereby improving learning outcomes.

**d)** Incentive mechanisms and self-regulation support: Through the analysis of network structure evolution, the sources of students' intrinsic motivation for autonomous learning can also be identified, thereby facilitating the design of appropriate incentive mechanisms. If the analysis indicates that certain students exhibit low engagement in the absence of external incentives, an incentive system can be implemented to stimulate their intrinsic motivation.

**e)** Feedback optimization and learning strategy adjustment: Based on the analysis of interactive feedback, teaching methods can be adjusted in a timely manner. If it is found that certain teaching approaches fail to effectively stimulate student participation, feedback strategies may be modified, such as enhancing student engagement through diverse interactive methods.

In summary, through the results of mobile network structure evolution analysis, both teachers and educational platforms can more precisely understand students' learning needs and behavioral changes, enabling the formulation of tailored learning support strategies for each student. These strategies can enhance students' intrinsic motivation for autonomous learning, increase their level of engagement and persistence in learning, and ultimately foster their autonomous learning abilities, leading to improved academic performance and greater learning autonomy.

## 6 EXPERIMENTAL RESULTS AND ANALYSIS

The data provided in Table 1 reveals a significant upward trend in the mobile network check-in activity. The table indicates substantial variations in the average number of new check-ins and new locations per day across different time periods, with both the total check-ins and locations increasing steadily over time. For instance, in certain periods (e.g., in columns 1 and 2), the daily increase in check-ins and locations approaches or exceeds 6,000, suggesting frequent usage of the mobile network platform by students. As time progresses, the total number of check-ins and locations continues to rise, reflecting a sustained increase in student engagement. Moreover, the total number of check-ins per location also exhibits notable variation, which may be attributed to the popularity of specific locations or the appeal of the teaching content associated with them. The rise in both check-in activity and interactive feedback suggests a growing level of student participation in the English writing teaching process, highlighting the effective role of the platform in fostering student engagement.

**Table 1.** Snapshot of mobile network check-in data for assisted English writing teaching

| Snapshot | Average Number of New Check-Ins Per Day | Average Number of New Locations Per Day | Total Number of Check-Ins | Total Number of Places |
|---|---|---|---|---|
| 1 | – | – | 178952 | 21255 |
| 2 | 6452 | 612 | 365421 | 41256 |
| 3 | 6125 | 658 | 523658 | 66253 |
| 4 | 6789 | 632 | 721356 | 87928 |
| 5 | 6235 | 648 | 832654 | 121252 |
| 6 | 6231 | 623 | 1123524 | 123252 |
| 7 | 6895 | 669 | 1213258 | 145285 |
| 8 | 6242 | 635 | 1236525 | 178952 |

The data presented in Figure 4 illustrates a distinct hierarchical distribution of the mobile network's scale in assisted English writing teaching. Specifically, the values for location-weighted and check-in-weighted networks are relatively high, at 250 and 300, respectively, highlighting the significant influence of location and check-in factors on student engagement and learning outcomes in the teaching process. In contrast, the unweighted values are comparatively lower, particularly in the case of large-scale users (greater than 1000), where the unweighted value is only 10. This suggests that, in large-scale applications, there may be issues of insufficient participation and uneven resource utilization.

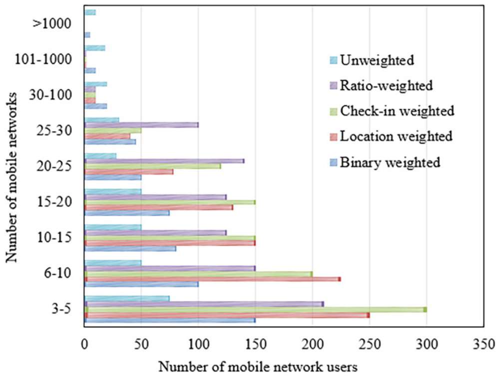



**Fig. 4.** Scale distribution of the mobile network for assisted English writing teaching

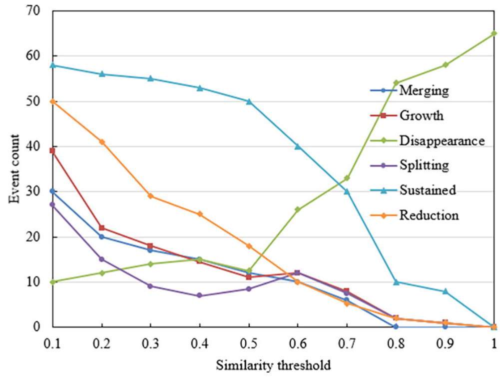



**Fig. 5.** Relationship between similarity threshold and event count in the mobile network evolution process

According to the data shown in Figure 5, as the similarity threshold increases, the number of events (merging, growth, disappearance, splitting, sustained, and reduction) during mobile network evolution exhibits distinct trends. At lower similarity thresholds (0.1 and 0.2), "merging" and "growth" events are more frequent, with counts of 30 and 39, and 20 and 22, respectively. This suggests that at lower thresholds, there is greater activity in node merging and network growth. However, as the similarity threshold gradually increases, particularly at values of 0.8 and 1.0, the "merging" and "growth" events nearly disappear, with counts approaching zero. In contrast, the number of "disappearance" events continuously increases as the similarity threshold rises, from 10 to 65. This increase is especially pronounced as the threshold approaches one. At the same time, "sustained" events are higher at lower thresholds (58 and 56) and gradually decrease as the threshold increases, eventually reaching zero. "Splitting" events occur more frequently at lower thresholds (27) but decrease significantly as the threshold increases, approaching zero. Finally, the number of "reduction" events also decreases progressively with the rise in the similarity threshold, dropping from 50 to zero. From the above data, it can be observed that the increase in similarity threshold has a clear impact on various events during mobile network evolution. At lower similarity thresholds (e.g., 0.1 and 0.2), "merging" and "growth" events are promoted, indicating that at low thresholds, there is a higher degree of similarity between nodes in the network, facilitating student interaction and collaboration. This could help students share resources and motivate each other in English writing learning. As the similarity threshold increases, the differences between nodes grow, leading to a decrease in "merging" and "growth" events, while "disappearance" events rise significantly. This reflects the fact that as student engagement changes, some learners or learning behaviors gradually withdraw from the network interaction. Particularly at higher similarity thresholds, student interaction decreases, leading to lower platform participation and a decline in the sustainability of learning activities. Moreover, the reduction in the number of "sustained" and "reduction" events also reveals that under high similarity conditions, some students or activities fail to remain active. This may suggest that, in such environments, students' motivation for autonomous learning and interactive engagement has been suppressed.

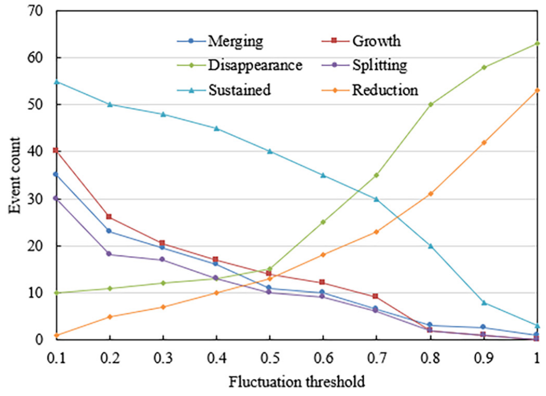



**Fig. 6.** Relationship between fluctuation threshold and event count in mobile network evolution

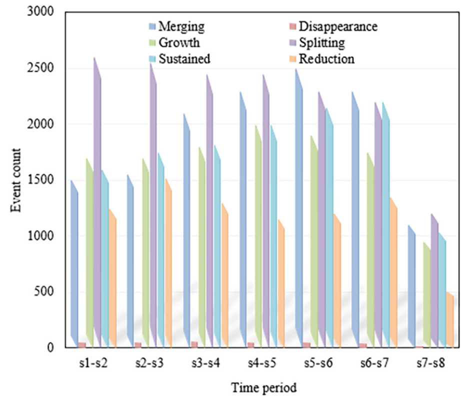



**Fig. 7.** Structural evolution analysis results in mobile network evolution

According to the data presented in Figure 6, as the fluctuation threshold increases, the number of events (merging, growth, disappearance, splitting, sustained, and reduction) in the mobile network evolution exhibits distinct trends. At lower fluctuation thresholds (0.1 and 0.2), "merging" and "growth" events occur more frequently, with counts of 35 and 40, and 23 and 26, respectively. These results reflect a closer interaction and information integration between nodes at lower thresholds. However, as the fluctuation threshold increases, the frequency of these events gradually decreases, reaching near-zero values when the threshold reaches one. In contrast, the number of "disappearance" events increases significantly with the rise in threshold, from 10 to 63, particularly at higher thresholds, indicating the negative impact of higher thresholds on certain behaviors. Additionally, the trends for "splitting" and "sustained" events are similar to those of "merging" and "growth" events; they occur more frequently at lower fluctuation thresholds but decrease as the threshold rises, ultimately approaching zero. The number of "reduction" events also follows a gradual upward trend, increasing from one to 53. From the data analysis, it can be inferred that the increase in fluctuation threshold has a significant effect on the learning behaviors within the mobile network. At lower fluctuation thresholds (0.1 and 0.2), the nodes within the network are denser, resulting in more frequent interaction and information sharing between students, which promotes the occurrence of "merging" and "growth" events. This suggests that in the context of English writing teaching, lower fluctuation thresholds may help enhance student collaboration and feedback, thereby improving overall learning outcomes. However, as the fluctuation threshold increases, particularly under higher threshold conditions (0.8 and 1.0), the connections between students become more distant, resulting in a decrease in interaction and a significant rise in the number of "disappearance" and "splitting" events. Under these higher thresholds, nodes within the network gradually lose their connections, and some students may "disappear" or "split" due to decreased participation, reflecting the suppressive effect of higher thresholds on platform activity. Furthermore, the increase in "sustained" and "reduction" events indicates changes in student engagement, with higher thresholds potentially leading to a decline in long-term participation, thereby affecting students' motivation and persistence in their learning.

Based on the data presented in Figure 7, the evolution of the mobile network over different time periods demonstrates a clear upward trend in the occurrences of merging and growth events, particularly during the s3–s4 and s4–s5 stages.

In these stages, the value of merging reached 2,300, while growth peaked at 2,000 in the s4–s5 period. This suggests that the application of the mobile network in English writing teaching has progressively deepened, contributing to the enhancement of teaching effectiveness. Simultaneously, the values for sustained and splitting also exhibited some fluctuations during the s3–s4 stage. Notably, splitting reached a high of 2,600 in the s1–s2 stage before gradually declining, reflecting the necessity of adjustments and optimizations to the teaching structure during the mobile network's application. A comprehensive analysis of these data leads to the conclusion that the integration of mobile networks into English writing teaching has not only fostered innovation in teaching methods but also enhanced students' autonomous learning abilities. Although occurrences of disappearance and reduction were observed during certain stages, the overall trend remains positive, indicating that educators should place greater emphasis on leveraging the advantages of mobile networks within instructional design and proactively address the challenges that arise. By continuously refining teaching strategies and utilizing the interactive feedback mechanisms of mobile networks, student motivation and writing skills can be effectively improved.

## 7 CONCLUSION

This study investigated the application and evolution of mobile networks in English writing teaching, proposing innovative solutions for optimizing teaching feedback and enhancing autonomous learning abilities through mobile network technology. From the experimental results, the evolutionary characteristics of the mobile network under different similarity and fluctuation thresholds, as well as structural evolution data, can provide valuable analytical tools for educators. During the teaching process, low similarity and fluctuation thresholds were found to facilitate interaction and collaboration among students, contributing to improved learning outcomes. As the thresholds increase, the connectivity between nodes gradually decreases, reflecting a reduction in student interactions and changes in learning behaviors, particularly the increase in "disappearance" and "splitting" events. This suggests that when using mobile networks to assist English writing teaching, careful attention should be paid to optimizing network structure and interaction design to avoid excessively low levels of student engagement.

However, several limitations exist within this study. The primary limitation is the insufficient personalized analysis of different student groups, particularly how similarity and fluctuation thresholds should be dynamically adjusted based on students' learning progress and ability levels. Additionally, although the models of network evolution and teaching feedback in the study provide preliminary references, they lack long-term tracking and validation with diverse data. Future research could further explore how personalized learning designs can be implemented by considering individual student differences and leveraging deep learning and artificial intelligence technologies to realize dynamic, intelligent teaching feedback. Furthermore, future studies should extend to interdisciplinary fields such as affective computing and gamified learning to further enhance students' autonomous learning motivation and writing abilities. Overall, this research provides an important theoretical basis and practical reference for exploring the application of mobile networks in English writing teaching, offering significant implications for promoting educational informatization and personalized learning.

## 8 REFERENCES


[1] D. Khamraeva, H. Hashim, and K. A. Jamaludin, "Mobile learning for transforming English writing skills: A systematic review (2013–2023)," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 19, pp. 4–17, 2024. https://doi.org/10.3991/ijim.v18i19.47729

[2] X. Liu, N. Abu Samah, and S. Md Salleh, "The impact of using a mobile app on improving students' creative thinking in business English writing with self-regulated learning," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 15, pp. 46–61, 2022. https://doi.org/10.3991/ijim.v16i15.31477

[3] H. Y. Lin and S. C. Tsai, "Student perceptions towards the usage of AR-supported STEMUP application in mobile courses development and its implementation into English learning," *Australasian Journal of Educational Technology (AJET)*, vol. 37, no. 3, pp. 88–103, 2021. https://doi.org/10.14742/ajet.6125

[4] S. P. Deore, "Human behavior identification based on graphology using artificial neural network," *Acadlore Transactions on AI and Machine Learning*, vol. 1, no. 2, pp. 101–108, 2022. https://doi.org/10.56578/ataiml010204

[5] I. Zulaeha, S. Subyantoro, C. Hasanudin, and R. Pristiwati, "Developing teaching materials of academic writing using mobile learning," *Ingénierie des Systèmes d'Information*, vol. 28, no. 2, pp. 409–418, 2023. https://doi.org/10.18280/isi.280216

[6] X. Q. Zhang, S. X. Wang, Y. L. Cao, and G. Q. Chen, "Application of analytical hierarchy process in teaching quality analysis of English writing," *International Journal of Emerging Technologies in Learning (IJET)*, vol. 15, no. 14, pp. 137–150, 2020. https://doi.org/10.3991/ijet.v15i14.15359

[7] P. J. Liu, "Intelligent optimization algorithm-driven informational teaching model for English reading and writing in universities," *Journal of Computational Methods in Sciences and Engineering*, vol. 24, no. 2, pp. 715–730, 2024. https://doi.org/10.3233/JCM-237101

[8] L. Han and J. Zhao, "Optimal allocation of mobile learning resources based on a complex network," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 17, no. 6, pp. 211–225, 2022. https://doi.org/10.3991/ijet.v17i06.30017

[9] D. Chen, X. Y. Guo, and C. Liu, "Research on the influencing factors of mobile learning behaviour: Taking the accounting learning app as an example," *International Journal of Mobile Communications*, vol. 22, no. 3, pp. 296–315, 2023. https://doi.org/10.1504/IJMC.2023.133223

[10] R. I. Kiconco, G. Rooks, and C. Snijders, "Learning mobile money in social networks: Comparing a rural and urban region in Uganda," *Computers in Human Behavior*, vol. 103, pp. 214–225, 2020. https://doi.org/10.1016/j.chb.2019.09.005

[11] K. Y. Tang, C. C. Chen, G. J. Hwang, and Y. F. Tu, "Did library learners benefit from m-learning strategies? Research-based evidence from a co-citation network analysis of the literature," *Educational Technology Research and Development*, vol. 70, pp. 1719–1753, 2022. https://doi.org/10.1007/s11423-022-10136-6

[12] S. Hopcan and S. T. Tokel, "Exploring the effectiveness of a mobile writing application for supporting handwriting acquisition of students with dysgraphia," *Education and Information Technologies*, vol. 26, pp. 3967–4002, 2021. https://doi.org/10.1007/s10639-021-10440-3

[13] A. M. Al-Abdullatif, M. A. Alsubaie, and E. A. Aldoughan, "Exploring the effects of excessive texting through mobile applications on students' technostress and academic writing skills in the Arabic language," *IEEE Access*, vol. 8, pp. 166940–166950, 2020. https://doi.org/10.1109/ACCESS.2020.3024021

[14] Y. Song, K. Sznajder, Q. Y. Bai, Y. Y. Xu, Y. F. Dong, and X. S. Yang, “English as a foreign language writing anxiety and its relationship with self-esteem and mobile phone addiction among Chinese medical students—A structural equation model analysis,” *PLoS One*, vol. 18, no. 4, p. e0284335, 2023. https://doi.org/10.1371/journal.pone.0284335

[15] W. Y. Zhou and X. S. Li, “Investigation of a Chinese character writing app: Learners’ perspectives,” *Knowledge Management & E-Learning*, vol. 14, no. 1, pp. 15–29. 2022. https://doi.org/10.34105/j.kmel.2022.14.002

[16] W. Y. Hwang, R. Nurtantyana, S. W. D. Purba, U. Hariyanti, Y. Indrihapsari, and H. D. Surjono, “AI and recognition technologies to facilitate English as foreign language writing for supporting personalization and contextualization in authentic contexts,” *Journal of Educational Computing Research*, vol. 61, no. 5, pp. 1008–1035, 2023. https://doi.org/10.1177/07356331221137253

[17] S. Ebadi and S. Bashir, “An exploration into EFL learners’ writing skills via mobile-based dynamic assessment,” *Education and Information Technologies*, vol. 26, pp. 1995–2016, 2021. https://doi.org/10.1007/s10639-020-10348-4

## 9 AUTHORS

**Weifeng Deng** is a doctorate candidate at DPU and is working as an Associate Professor. She graduated from the English Department of Hebei Normal University with a master’s degree in English Language and Literature in 2002. She has worked at Hainan Vocational University of Science and Technology and published more than 10 papers (E-mail: 893094362@qq.com).

**Lin Wang** (Ph.D., Professor), is selected as the high-level talent in Hainan Province. He is the creator of Neutralization System, Tai Chi Yoga, Class I instructor of National Health Qigong, psychological counsellor, and senior Yoga Instructor. He has more than ten years of experience in teaching Tai Chi abroad, and is engaged in theoretical practice and research development of Tai Chi yoga, meditation and decompression, Health Qigong, physical and mental growth. He has published several papers at home and abroad, including 15 monographs and 10 papers included in international conferences, presided over two provincial-level projects, and won six national second prizes and six third prize for his papers. He has worked in Hainan Vocational University of Science and Technology (E-mail: wanglintaichi@163.com).