

PAPER

Mobile Technology-Enabled Classroom Interaction: Advancing Interactive Learning in Higher Education

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Amid the rapid advancement of information technology, mobile technology—characterized by its portability, real-time functionality, and interactive capacity—has been increasingly leveraged to transform models of classroom interaction in higher education. Traditional lecture-based instruction has encountered growing demands for innovation, while the widespread adoption of mobile devices and applications has not only altered students' learning behaviors but also introduced novel interaction scenarios between teachers and students. However, significant methodological limitations remain in existing studies. Many rely predominantly on traditional survey-based approaches to examine teacher-student interaction, which are insufficient for capturing the dynamic complexity and real-time characteristics of mobile-mediated interaction networks. Furthermore, most investigations into temporal features of interaction remain confined to descriptive statistics, lacking deeper insights into burstiness and memory effects. Focusing on interactive learning in higher education classrooms through the lens of mobile interaction networks, two principal dimensions were explored in this study. First, teacher-student interaction patterns were analyzed by examining overall and individual network structural characteristics, as well as interaction dynamics, through social network analysis to uncover node connectivity patterns and interaction intensity. Second, temporal characteristics of interaction were investigated via time series analysis, with an emphasis on identifying burstiness and memory-related patterns. By integrating structural and temporal dimensions, this study aims to establish a theoretical foundation for the development of mobile technology-enabled interactive learning models. The findings are intended to inform pedagogical strategy optimization and enhance classroom interaction effectiveness while also providing practical guidance for the improvement of mobile educational applications.

KEYWORDS

mobile technology, classroom interaction, higher education, interactive learning, social network analysis, time series analysis

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1 INTRODUCTION

With the rapid development of information technology, mobile technologies—such as smartphones, tablets, and various mobile applications—have been profoundly reshaping the ways in which individuals live and learn [1–4]. In the field of higher education, traditional classroom-based instructional models have been increasingly challenged by the demand for innovation and transformation [5–7]. The integration of mobile technology has opened new possibilities for classroom interaction [8, 9]. As mobile internet usage becomes more widespread and mobile devices are adopted on a large scale, students' in-class learning behaviors and modes of interaction have undergone significant changes [10–13]. Mobile technologies, distinguished by their portability, real-time capabilities, and interactive features [14, 15], have enabled more flexible and diverse learning experiences for students and have created novel pathways and platforms for teacher-student interaction. Against this backdrop, investigating the integration of mobile technology into classroom interaction and constructing new models of interactive learning suitable for higher education have become topics of pressing relevance.

A growing body of scholarly work has addressed the intersection of mobile technology and classroom interaction. However, methodological limitations are evident in several existing studies. For example, in the analysis of teacher-student interaction dynamics, Rimm-Kaufman et al. [16] relied solely on traditional questionnaire-based approaches, which are limited in their ability to comprehensively and deeply uncover the complex relational structures and interactional characteristics embedded within mobile interaction networks. Such approaches depend heavily on participants' self-reporting, introducing potential subjective bias and failing to capture real-time and dynamic interaction processes. Furthermore, when investigating the temporal characteristics of classroom interaction, most existing studies have focused on descriptive statistics [17, 18], lacking deeper exploration into burstiness and memory effects. As a result, the underlying mechanisms and evolving patterns of classroom interaction in mobile technology-enabled environments remain insufficiently understood.

The present study is structured around two primary lines of inquiry. The first focuses on the analysis of teacher-student interaction within classroom settings, as mediated by mobile interaction networks. This includes an examination of overall network structural characteristics, individual network structural properties, and the dynamic attributes of interaction within the network. By constructing a mobile interaction network model and applying social network analysis techniques, teacher-student relationships under mobile technology-enabled environments were investigated in depth. Emphasis is placed on revealing patterns of node connectivity, measures of centrality, as well as the intensity and frequency of interactions. The second line of inquiry centers on the temporal characteristics of teacher-student interaction, as observed within mobile interaction networks. Particular attention is given to the analysis of burstiness and memory effects in interaction time patterns. Through time series analysis of interaction sequences, the temporal distribution and evolving trends of interactive behavior were extracted, along with the extent to which past interaction events influence subsequent engagement.

2 ANALYSIS OF TEACHER-STUDENT CLASSROOM INTERACTION BASED ON MOBILE INTERACTION NETWORKS

2.1 Analysis of overall network structural characteristics

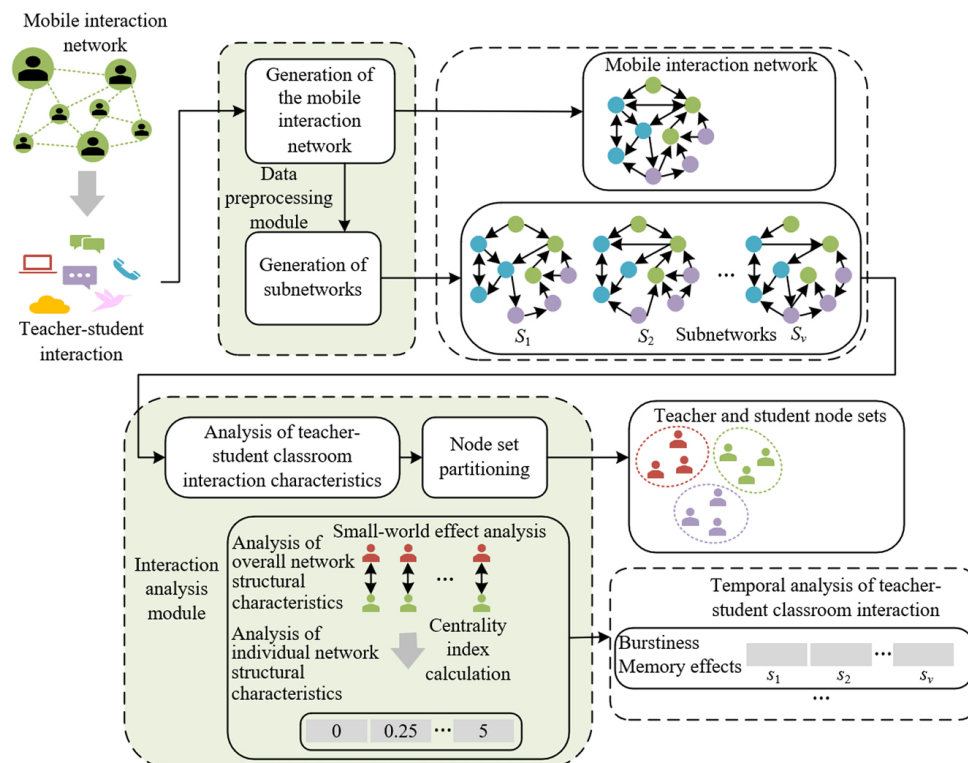


Fig. 1. Analytical framework for teacher-student classroom interaction based on mobile interaction networks

Figure 1 illustrates the analytical framework for investigating teacher-student classroom interaction based on mobile interaction networks. From the perspective of overall network structure, teacher-student interactions shaped by mobile interaction networks exhibit characteristics that are markedly distinct from those observed in traditional classroom settings. Under the influence of mobile technology, the resulting interaction networks demonstrate increased connectivity density and dynamic openness. Various mobile applications have eliminated the spatiotemporal constraints of conventional classrooms, enabling information exchange between teachers and students, as well as among students themselves, to transcend unidirectional or linear communication models. A multidimensional network structure has thus emerged, characterized by multi-node coordination. Interactive features such as real-time comment streams, collaborative group task platforms, and instant Question and Answer (Q&A) systems have driven a shift from teacher-centered “star-shaped structures” to network-based configurations emphasizing bidirectional teacher-student interaction and diversified student connectivity. The network density metric serves as an intuitive indicator of the enhanced interaction frequency facilitated by mobile technology. As mobile devices have become the primary medium of interaction, students are able to participate in real time through multimodal forms such as text, voice, and video. This significantly increases the number of edges within the network and promotes a transition from “teacher-dominated output” to “collaborative node activation.” Furthermore, the degree centrality distribution within mobile interaction

networks shows a trend toward greater balance. The absolute centrality traditionally occupied by teacher nodes is attenuated, while the activity level and connectivity capacity of student nodes are amplified through mobile technology. As a result, a “multi-centered” network structure has taken shape, composed of both teacher nodes and highly active student nodes. This structural transformation reflects the reconfiguration of classroom power dynamics driven by mobile technology.

The overall structure of the mobile interaction network also reveals distinct features of interactional diversity and hierarchical organization. In traditional classroom environments, teacher-student interactions are predominantly centered on instructional content delivery. In contrast, mobile technology-enabled networks encompass a wider range of interaction types, including knowledge inquiry, emotional exchange, and task-oriented collaboration. These diverse interactional edges interweave to form a complex and multifaceted network. Functional modules such as assignment discussion forums on mobile learning platforms, group communication channels for collaborative projects, and real-time classroom polling systems have addressed various interactional needs, leading to a modular, clustered structure within the network. Depending on the nature of their interactional goals, students can form temporary or persistent subnetworks characterized by high internal connectivity. These subnetworks are interconnected through teacher nodes or core student nodes, enabling cross-module interactions. Such a configuration preserves the guiding role of teachers in central instructional tasks while simultaneously empowering students to construct self-organized learning communities. This dual functionality highlights the capacity of mobile interaction networks to support both personalized and collaborative learning. Structural hole analysis further indicates that mobile technology can effectively reduce redundant intermediary nodes in information transmission, thereby enhancing the bridging function of key nodes. As a result, interactional information within the classroom can circulate more efficiently throughout the network, ultimately improving the effectiveness of overall classroom interaction.

Based on the analysis above, the mobile interaction network constructed within the classroom context demonstrates a typical small-world effect, characterized by high clustering coefficients and short path lengths. On the one hand, strong local clustering can be observed within the network, as students form tightly connected subnetworks based on shared learning objectives, interests, or collaborative tasks. For example, temporary communities are formed within course discussion groups and collaborative platforms. Within these clusters, high-frequency interactions take place, resulting in locally dense connections. On chapter-specific discussion boards of mobile learning applications, students are engaged in real-time Q&A and idea exchange around specific knowledge points. In collaborative assignment modules, frequent interaction among group members can produce clustering coefficients significantly higher than those found in traditional classrooms structured by seating arrangements or static grouping, which typically exhibit looser connectivity. These clustering patterns not only reinforce the learning community’s awareness of the student group but also create a micro-ecology conducive to deep knowledge construction. Repeated interaction within clusters facilitates cognitive alignment, thereby accelerating the local evolution of knowledge networks. On the other hand, teacher nodes and highly active student nodes function as bridges across distinct subnetworks, ensuring low network fragmentation. Teachers facilitate global connectivity through practices such as simultaneous multi-group Q&A and cross-group progress coordination, effectively linking otherwise isolated subnetworks into a cohesive whole. This configuration mitigates the risk of informational silos caused by local clustering and allows the network to retain high clustering while maintaining overall connectivity.

The short path length characteristic of the mobile interaction network reflects the high efficiency of classroom information transmission. In traditional classrooms, student interactions with teachers or peers have typically relied on limited physical channels such as raising hands during class or consulting privately after class. These methods involve long information transmission paths and are constrained by time and space. In contrast, under mobile technology-enabled environments, real-time messaging tools and interactive platforms eliminate spatiotemporal barriers, resulting in significantly reduced average path lengths between any two nodes. In live-streamed classes, for instance, students pose questions via real-time comment functions, to which teachers can respond immediately and directly tag the relevant student. Alternatively, peers may join the discussion by quoting the reply. Such multi-directional interaction patterns allow information to circulate in a closed loop within short sequences of “question–response–expansion,” without passing through multiple intermediary nodes. Moreover, supernodes within the mobile interaction network further optimize the path structure. These nodes, characterized by high degrees of connectivity, act as hubs within the network, enabling indirect nodes to be connected through only one or two intermediaries. This configuration exemplifies the micro-level manifestation of the “six degrees of separation” phenomenon observed in small-world networks. The short path length property not only enhances the immediacy of classroom interaction but also facilitates the cross-cluster flow of heterogeneous information. As a result, various resources—ranging from domain-specific knowledge to emotional support—can be disseminated across the network in a highly efficient manner, thereby increasing the overall effectiveness of classroom interaction. The following Equation (1) presents the formal calculation of the small-world effect index T :

$$T = \frac{Catual/Crandom}{Latual/Lrandom} \quad (1)$$

2.2 Analysis of individual network structural characteristics

An analysis of individual network characteristics was conducted within both the overall teacher-student mobile interaction network and the subnetworks corresponding to each student group, focusing on three centrality indicators: degree centrality, betweenness centrality, and eigenvector centrality. In mobile interaction networks, degree centrality reflects the frequency and breadth of direct interactions initiated by a node and serves as a core indicator of individual activeness within local network structures. Teacher nodes typically exhibit higher degree centrality, as they frequently initiate interactions through task assignment, real-time responses, and discussion facilitation. These actions enable the formation of direct connections with multiple student nodes, positioning teacher nodes as “strong hubs” in classroom interaction. Specifically, let $Z_{XF}(a)$ denote the absolute degree centrality of node a , and let v represent the size of the network. The following expression provides the calculation formula for $Z_{XF}(a)$:

$$Z'_{EF}(a) = \frac{Z_{XF}(a)}{(2v - 2)} \quad (2)$$

In mobile learning platforms, each time a teacher posts a global announcement using an @all-students tag or delivers personalized feedback to individual students, the corresponding degree centrality increases, highlighting the teacher’s role in information dissemination across the network. Within subgroup networks, students

with higher degree centrality are often initiators or active contributors to group tasks. For instance, students who frequently share resources or coordinate discussions in group communication channels are characterized by elevated degree centrality, which not only reflects proactive engagement but also enhances the internal information flow of the subnetwork. The multimodal interactive features of mobile technology further amplify disparities in degree centrality. Highly active nodes maintain dense connections through diverse forms of interaction, while low-activity nodes, constrained by infrequent engagement, are more likely to occupy peripheral positions within the network. This variation provides a quantitative basis for identifying “interaction cores” and “potentially silent groups” in classroom settings.

Betweenness centrality measures the extent to which a node functions as an intermediary or bridge within a network, thereby reflecting its capacity to control the flow of information. In the overall structure of mobile interaction networks, teacher nodes have typically occupied positions of high betweenness centrality, particularly in cross-subnetwork information transmission, where they serve as essential conduits. Let Z_{xyu} denote the absolute centrality of a node, and v represent the network size. The calculation formula for Z_{EYu} is given as follows:

$$Z_{EYu} = \frac{2Z_{xyu}}{v^2 - 3v + 2} \quad (3)$$

When learning groups develop distinct discussion focuses within their respective subnetworks, teachers frequently consolidate these divergent topics and respond across multiple groups or redistribute high-quality learning resources from one subnetwork to others. Through such practices, teachers function as structural hole fillers, mitigating the risk of network fragmentation. Certain highly active student nodes also demonstrate notable levels of betweenness centrality. For instance, students who actively participate across multiple group discussion forums or those who effectively reinterpret teachers’ explanations into more accessible language for peers—serving as knowledge translators—contribute to shortening the information transmission path between heterogeneous subnetworks. Within individual subnetworks, nodes with elevated betweenness centrality often serve as coordinators. These may include students responsible for aggregating group opinions or aligning group work with teacher requirements. By assuming intermediary roles, such nodes help sustain internal connectivity and prevent interactional discontinuities caused by coordination failures. The real-time and cross-platform nature of mobile technologies further enables intermediary nodes to transcend the spatial and temporal limitations of physical classrooms. Whether in synchronous or asynchronous settings, these nodes continue to serve as bridging agents, becoming key structural anchors for maintaining global connectivity across the network.

2.3 Analysis of interaction characteristics

To analyze teacher-student interaction characteristics within the classroom, the E-I index from social network analysis was introduced. The E-I index quantifies the relative intensity of interactions between different categories of nodes versus within the same category, thereby revealing the network’s tendency toward intergroup connectivity. The core principle involves partitioning the classroom interaction network into two distinct sets: a teacher node set and a student node set. By calculating the ratio of intergroup interaction edges to intragroup interaction edges, the relative strength of teacher-student interaction within the overall network is assessed.

Let RM denote the coefficient of intergroup relations and UM the coefficient of intragroup relations. The E-I index is defined by the following equation:

$$E-I = \frac{RM - UM}{RM + UM} \tag{4}$$

In mobile interaction networks, although the role boundaries between teachers and students have become increasingly blurred due to technological affordances, essential differences in interaction attributes persist. Teacher nodes typically perform authoritative functions such as knowledge transmission and rule setting, while student nodes primarily engage in knowledge reception and collaborative construction. The introduction of the E-I index enables precise identification of interaction patterns under such role differentiation. When the frequency of cross-category interactions between teachers and students exceeds that of same-category interactions among students, the E-I index yields a positive value with increasing absolute magnitude, indicating a strong outward-oriented interaction pattern. Conversely, if students tend to form closed interaction loops predominantly within their own category, the E-I index approaches zero or becomes negative, reflecting an inward-oriented interaction tendency within the network.

3 TEMPORAL ANALYSIS OF TEACHER-STUDENT CLASSROOM INTERACTION BASED ON MOBILE INTERACTION NETWORKS

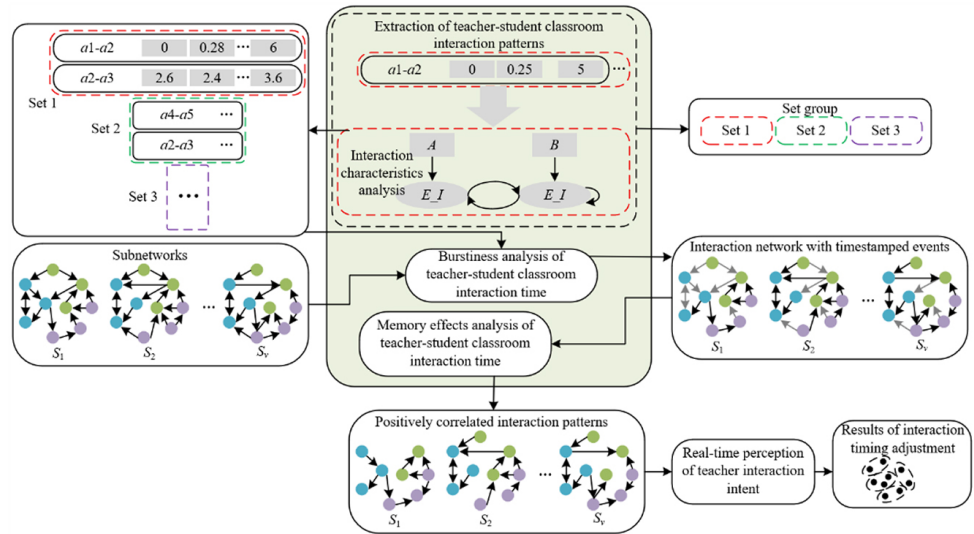


Fig. 2. Principle of temporal analysis of teacher-student classroom interaction based on mobile interaction networks

Figure 2 illustrates the analytical framework for examining the temporal characteristics of teacher-student classroom interaction in the context of mobile interaction networks. Within such networks, the timing of classroom interaction events demonstrates a marked burstiness—characterized by clustered patterns of activity that alternate between high and low frequency over time. This bursty distribution arises from both structured influences, such as instructional design, and unstructured drivers, such as user behavior patterns enabled by mobile technologies. Let the standard deviation of the inter-event time series π be denoted by δ_π , and let the mean of the inter-event time series s be represented by l_π . Burstiness is quantitatively

measured using the indicator Y , as defined by Goh and Barabási, with the following formulation:

$$Y = \frac{\delta_{\pi} - l_{\pi}}{\delta_{\pi} + l_{\pi}} \quad (5)$$

Specifically, during live-streamed instructional sessions, high-frequency synchronous interactions between teachers and students are facilitated through features such as real-time comment streams and audio connections. These interactions tend to occur in short, densely packed intervals, forming pronounced temporal peaks. In contrast, during the hours following a session, students may initiate asynchronous inquiries—often triggered by reviewing notes or completing assignments—through private messaging functions on mobile learning applications, giving rise to secondary interaction peaks. These temporal clusters are closely associated with the portability of mobile devices, which enables interaction to occur opportunistically during fragmented periods such as commuting or between classes. As a result, interaction events that would traditionally follow a linear distribution in physical classroom settings are transformed into burst-like pulses governed by technological accessibility. The quantification of burstiness patterns can be further refined through the fitting of probability density functions to the inter-event time distributions. A typical empirical signature is the disproportionately high probability of short inter-event intervals, exceeding expectations under an exponential distribution, thereby indicating a strong temporal clustering tendency inherent in mobile interaction networks.

The inter-event intervals of teacher-student interactions within mobile interaction networks demonstrate a significant memory effect, indicating a temporal dependency between current and past behaviors. The timing of a given interaction is influenced by preceding interaction patterns, resulting in varying durations of subsequent intervals. This memory effect manifests in two distinct ways: as a positive reinforcement effect and a negative attenuation effect. In the case of positive reinforcement, when a teacher responds promptly to a student inquiry, an “immediate feedback expectation” may be established, leading to shorter intervals before the next interaction. This forms a positively correlated sequence such as “short interval \rightarrow short interval.” Conversely, when a teacher’s response is delayed, students may reduce their frequency of engagement, resulting in prolonged intervals—indicative of a negative attenuation pattern. Let the teacher-student classroom interaction sequence be denoted by the ordered time series $\{s_1, s_2, \dots, s_{v_{\pi}}\}$, where l_1 and l_2 represent the means of two respective segments of the sequence, and δ_1 and δ_2 denote their standard deviations. The sequence of inter-event intervals $\{\pi_1, \pi_2, \dots, \pi_{v_{\pi}}\}$ is obtained by computing the differences between consecutive elements. The total number of intervals is represented by v_{π} , and the sequence is divided into two groups: $\{\pi_1, \pi_2, \dots, \pi_{v_{\pi}-1}\}$ and $\{\pi_1, \pi_2, \dots, \pi_{v_{\pi}}\}$. The memory coefficient L , proposed by Goh and Barabási, is used to quantify the memory effect, and is defined as follows:

$$L = \frac{1}{v_{\pi} - 1} \sum_{u=1}^{v_{\pi}-1} \frac{(\pi_u - l_1)(\pi_{u+1} - l_2)}{\delta_1 \delta_2} \quad (6)$$

When $L > 0$, the sequence is said to exhibit positive memory, with greater values indicating stronger temporal dependence. Conversely, $L < 0$ reflects negative memory. For example, if a student receives a teacher’s reply within five minutes after the first inquiry via instant messaging tools, the average time before the second question may be reduced to under ten minutes. However, if the first response takes more than thirty minutes, the interval before the next inquiry may exceed one hour.

The visibility of online status, afforded by mobile platforms, further reinforces this memory effect. Students can perceive the teacher’s availability and interaction intent in real time and adapt their engagement timing accordingly. The identification of memory patterns can be validated using autocorrelation functions or generalized additive models. The core value of this analysis lies in its capacity to reveal the dynamic strategic behavior underlying teacher-student interactions in mobile contexts. Under the mediation of technology, interaction time becomes not merely a physical measurement but also the outcome of strategic timing decisions informed by perceived responsiveness. These insights provide a temporal basis for optimizing real-time interaction design in mobile-enhanced learning environments.

4 EXPERIMENTAL RESULTS AND ANALYSIS

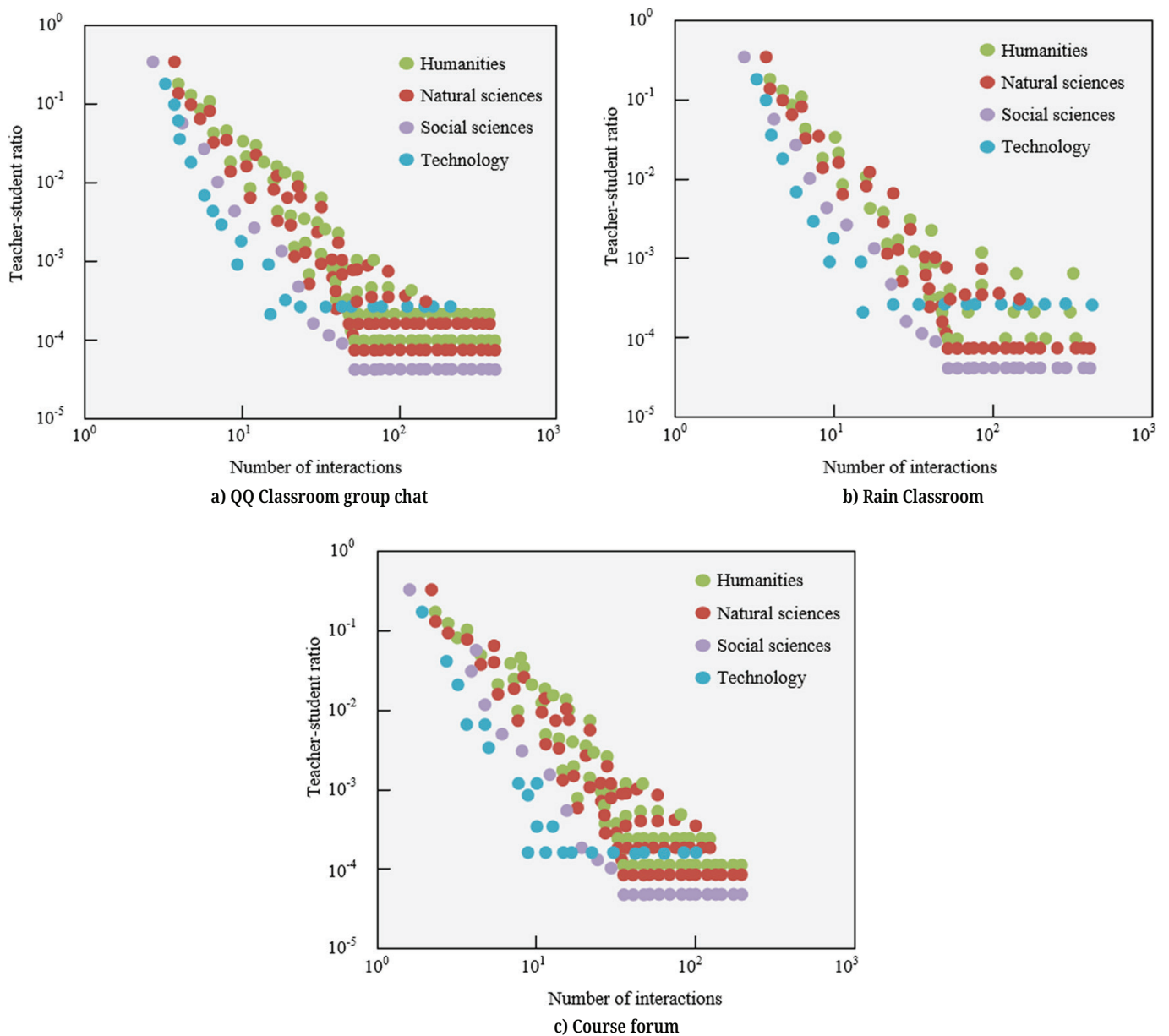


Fig. 3. Distribution of teacher-student interactions across disciplines in different mobile interaction network platforms

As shown in Figure 3, under three types of mobile interaction network scenarios—QQ Classroom group chat, Rain Classroom, and course forums—a power-law distribution was observed in the frequency of teacher-student interactions across different disciplines. As the number of interactions increased, the overall proportion of teacher-student interactions demonstrated a downward trend. This reflects a typical pattern in mobile interaction networks: a small number of high-interaction cases correspond to a lower teacher-student ratio, while a large number of low-interaction cases correspond to a higher teacher-student ratio. This pattern indicates that peer-to-peer interaction becomes increasingly active as the total volume of interaction grows, while the relative proportion of teacher-student interactions undergoes dynamic adjustment. Significant disciplinary differences were identified. In the natural sciences, interaction frequencies covered a broader range across all platforms, with more pronounced proportional shifts, suggesting a higher degree of diversity and engagement in mobile interaction behavior. In contrast, disciplines in technology exhibited a more stable teacher-student ratio in the later phases of interaction, particularly on platforms such as QQ Classroom group chats, reflecting a more regularized interaction pattern. Disciplines within the humanities and social sciences displayed relatively concentrated distributions and less varied interaction modes. In line with the study's broader analytical framework, these findings reveal the disciplinary dependency of mobile interaction networks. Due to differences in the nature of knowledge and communication habits, interaction patterns across disciplines vary in terms of node connectivity, centrality, and interaction intensity. Further analysis indicated that mobile interaction networks exhibit a self-organized, scale-free topology, while temporal features such as burstiness and memory effects are reflected in the dynamic shifts observed within the data distribution.

Table 1. Top 10 degree centrality rankings in classroom-based mobile interaction networks across disciplines

Rank	Humanities		Natural Sciences		Social Sciences		Technology	
	<i>Id</i>	Degree Centrality	<i>Id</i>	Degree Centrality	<i>Id</i>	Degree Centrality	<i>Id</i>	Degree Centrality
1	ZU1_19	0.0412	ZU7_29	0.0125	ZU1_19	0.0825	ZU10_186	0.0426
2	ZU2_37	0.0418	ZU1_38	0.0097	ZU2_37	0.0315	ZU3_44	0.0178
3	ZU3_44	0.0236	ZU9_238	0.0092	ZU15_1164	0.0287	ZU10_159	0.0126
4	ZU4_23	0.0225	ZU5_5	0.0091	ZU10_186	0.0225	ZU9_245	0.0114
5	ZU5_5	0.0178	ZU2_37	0.0088	ZU10_159	0.0189	ZU7_29	0.0114
6	ZU4_47	0.0179	ZU6_21	0.0076	ZU15_2384	0.0125	ZU7_63	0.0112
7	ZU14_4	0.0156	ZU1_47	0.0073	ZU11_101	0.0114	ZU9_212	0.0094
8	ZU14_332	0.0123	ZU9_404	0.0071	ZU12_56	0.0112	ZU1_19	0.0091
9	ZU12_120	0.0125	ZU7_78	0.0066	ZU1_12	0.0123	ZU6_3	0.0087
10	ZU13_15	0.0138	ZU5_15	0.0066	ZU10_209	0.0114	ZU9_404	0.0077

Analysis of the data presented in Table 1 reveals significant disciplinary variation in degree centrality within classroom-based mobile interaction networks. Nodes in the social sciences exhibited substantially higher levels of activity and connectivity, indicating a strong dependence on highly active individuals to drive information diffusion. This pattern suggests a teacher-student interaction model centered around

key nodes. In contrast, natural sciences displayed generally lower degree centrality values with relatively small variation among the top-ranking nodes. This uniformity suggests a more balanced distribution of activity across nodes, emphasizing collaborative group behavior over individual dominance. It may also imply a greater reliance on betweenness centrality rather than degree centrality. Humanities and technology disciplines demonstrated intermediate characteristics. The difference in activity between core and non-core nodes was moderate, indicating an interaction model that balances individual activeness with collective collaboration. Taken together with the broader findings of the study, these results support the following insight: Disciplinary characteristics exert a profound influence on the structural properties of individual nodes within mobile interaction networks.

Table 2. Top 10 betweenness centrality rankings in classroom-based mobile interaction networks across disciplines

Rank	Humanities		Natural Sciences		Social Sciences		Technology	
	<i>Id</i>	Betweenness Centrality	<i>Id</i>	Betweenness Centrality	<i>Id</i>	Betweenness Centrality	<i>Id</i>	Betweenness Centrality
1	ZU1_37	0.00223	ZU1_38	0.00112	ZU1_19	0.01256	ZU7_63	0.01255
2	ZU2_74	0.00221	ZU2_37	0.00098	ZU15_693	0.00268	ZU1_19	0.00265
3	ZU4_23	0.00178	ZU5_44	0.00085	ZU2_74	0.00256	ZU2_10	0.00254
4	ZU8_5	0.00073	ZU9_172	0.00051	ZU2_17	0.00224	ZU9_212	0.00223
5	ZU1_19	0.00087	ZU9_238	0.00037	ZU15_171	0.00223	ZU7_29	0.00228
6	ZU1_121	0.00023	ZU7_54	0.00036	ZU15_116	0.00189	ZU3_3	0.00189
7	ZU4_79	0.00022	ZU7_78	0.00032	ZU2_67	0.00132	ZU9_670	0.00135
8	ZU3_44	0.00021	ZU9_33	0.00028	ZU2_13	0.00128	ZU9_197	0.00128
9	ZU2_16	0.00009	ZU2_8	0.00023	ZU10_209	0.00088	ZU6_3	0.00088
10	ZU3_26	0.00006	ZU16_25	0.00015	ZU2_83	0.00074	ZU5_5	0.00076

Table 3. Top 10 eigenvector centrality rankings in classroom-based mobile interaction networks across disciplines

Rank	Humanities		Natural Sciences		Social Sciences		Technology	
	<i>Id</i>	Eigenvector Centrality	<i>Id</i>	Eigenvector Centrality	<i>Id</i>	Eigenvector Centrality	<i>Id</i>	Eigenvector Centrality
1	ZU1_19	1.0101	ZU7_78	1.0002	ZU1_19	1.0002	ZU10_168	1.0001
2	ZU14_61	0.6785	ZU7_29	0.9852	ZU15_1164	0.4325	ZU3_44	0.3652
3	ZU14_69	0.4256	ZU11_170	0.5841	ZU10_186	0.3253	ZU7_29	0.3254
4	ZU4_23	0.4152	ZU1_38	0.5326	ZU2_37	0.3125	ZU10_159	0.3125
5	ZU14_4	0.3562	ZU2_37	0.5126	ZU15_2384	0.3125	ZU9_245	0.2236
6	ZU2_37	0.3425	ZU16_651	0.4582	ZU10_159	0.3156	ZU7_63	0.2248
7	ZU12_121	0.3125	ZU5_44	0.4326	ZU10_209	0.2236	ZU9_404	0.1652
8	ZU5_44	0.3256	ZU13_9	0.4256	ZU11_101	0.2255	ZU9_212	0.1625
9	ZU5_5	0.3286	ZU16_1739	0.4125	ZU15_780	0.1895	ZU9_102	0.1689
10	ZU4_47	0.2896	ZU16_35	0.3789	ZU15_1669	0.1854	ZU2_10	0.1596

Analysis of the data in Table 2 reveals significant disciplinary variation in betweenness centrality within mobile interaction networks for classroom learning. In the social sciences, core nodes exhibited prominent intermediary roles, acting as critical bridges for cross-subnetwork information flow. This indicates a strong dependence on hub-like nodes to integrate and distribute diverse forms of information, aligning with the relational and dialogic nature of knowledge construction in the social sciences. In contrast, nodes in the natural sciences displayed generally low betweenness centrality values, suggesting a network topology that favors direct connections between nodes. This pattern reflects the logical and practice-oriented characteristics of knowledge exchange in scientific disciplines, where reliance on intermediary nodes is minimized. Disciplines in the humanities and technology exhibited intermediate levels of betweenness centrality. This indicates that while information hubs are present, direct interaction patterns are also retained. Such a structure reflects a hybrid model in which intermediary coordination and task-driven exchange coexist and complement each other to meet diverse interaction needs.

Analysis of the data presented in Table 3 reveals both disciplinary distinctions and cross-cutting patterns in eigenvector centrality within mobile interaction networks. Across all disciplines, core nodes exhibited high eigenvector centrality values, indicating that such nodes were not only widely connected but also closely linked to other influential nodes. This pattern highlights the critical role of high-quality connections in facilitating academic knowledge dissemination within mobile environments. Distinct disciplinary characteristics were also observed. In the humanities and natural sciences, eigenvector centrality values were notably higher, suggesting that knowledge construction in these domains was driven by deep academic engagement. Core nodes attracted other high-impact nodes through high-value content, thus promoting vertical knowledge deepening. By contrast, eigenvector centrality was found to be more evenly distributed in the social sciences, reflecting the field's emphasis on openness, pluralistic perspectives, and interaction diversity. In such networks, the horizontal diffusion of ideas was fostered by the dynamic exchange among multiple moderately influential nodes. In technology disciplines, core nodes were found to facilitate knowledge transmission through practical interaction modes, including tool demonstrations and problem-solving guidance. These interactions enhanced both the practicality and efficiency of technical knowledge acquisition.

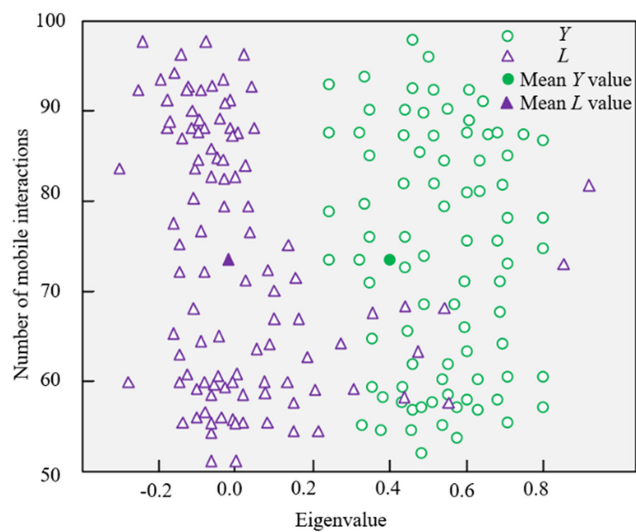


Fig. 4. Burstiness and memory distribution of single teacher-student classroom interaction time intervals

These results underscore two key insights: 1) Eigenvector centrality is deeply coupled with the disciplinary logic of knowledge dissemination. In the humanities and natural sciences, knowledge is vertically deepened through intensive interactions with core nodes. In the social sciences, lateral expansion is supported by diverse peer-level engagement. In technology disciplines, core nodes guide practice-based learning through demonstrative leadership. 2) Within mobile interaction networks, eigenvector centrality serves not only as a quantitative indicator of node influence but also as a reflection of the underlying epistemic models of each discipline. As such, it provides valuable input for discipline-specific optimization of instructional design. For instance, the humanities and natural sciences may benefit from reinforcing deep engagement with central nodes, the social sciences from fostering heterogeneous participation, and the technology domain from emphasizing technical modeling through core node exemplars.

As illustrated in Figure 4, a significant association between the burstiness index (Y) and the memory coefficient (L) was identified within the time interval distributions of single-session teacher-student interactions. The values of Y were predominantly concentrated in the 0.4–0.8 range, corresponding to 60–90 mobile interactions. This indicates pronounced temporal clustering, reflecting the enhanced aggregation of interaction time enabled by mobile technologies. The values of L ranged from -0.2 to 0.8 , with associated interaction frequencies between 50 and 90. When L was negative, lower interaction frequencies were observed, suggesting that prior delays in interaction tended to lengthen subsequent intervals. In contrast, positive L values were associated with higher interaction frequencies, indicating that rapid prior exchanges stimulated subsequent high-frequency interactions. As shown in Figure 4, considerable disciplinary differences emerged in both burstiness and memory characteristics. In terms of burstiness, higher average Y values were observed in natural sciences and social sciences, implying that interactions within these disciplines were more likely to form temporally dense clusters. Conversely, humanities and technology exhibited lower Y values, indicating weaker temporal aggregation of interaction events. Regarding memory, the natural sciences showed negative L values, suggesting that previous interactions exerted a delaying effect on future ones. Social sciences and technology displayed memory coefficients near zero, indicating neutral memory effects. In contrast, humanities exhibited positive L values, signifying the presence of positive memory.

5 CONCLUSION

This study examined classroom interaction empowered by mobile technologies from the dual perspectives of relational structure and temporal dynamics. Through social network analysis, the mobile interaction network was characterized by polycentric and modular features, with clear disciplinary distinctions observed in individual centrality measures. Interaction intensity, frequency, and connection patterns of nodes were quantitatively analyzed. In parallel, time series analysis revealed the presence of burstiness and memory effects in teacher-student interactions, both of which were shown to vary significantly by discipline. The primary contribution lies in offering theoretical foundations for discipline-specific mobile instructional design, thereby supporting the pedagogical shift from unidirectional lecturing to dynamic, technology-mediated interaction. Nonetheless, several limitations were acknowledged, including the narrow scope of interaction contexts, the use of static methods, and the limited disciplinary sampling. Future investigations

are encouraged to incorporate multimodal and cross-platform data, adopt dynamic modeling frameworks, and introduce AI-driven adaptive interventions. Such extensions are expected to strengthen disciplinary adaptability and foster the development of a fully integrated, intelligent learning ecosystem. By further enhancing the effectiveness of mobile technologies in higher education, this line of inquiry may contribute to the innovation of personalized and efficient instructional models, offering broader theoretical and practical references for the ongoing digital transformation of education.

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