

Large-Scale Behavioral Network Analysis: Unveiling the Impact of the COVID-19 Pandemic on University Student Interactions

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Abstract

This study examines the structural evolution and behavioral regularity of student social networks before, during, and after COVID-19. Using 65 million campus smart-card transactions (2019–2024), we constructed temporal friendship networks and applied motif detection with behavioral orderliness analysis. Results show stage-specific impacts of the pandemic. During Spring 2020, clustering coefficients, entropy, and average degree dropped sharply, reflecting a collapse of established social structures. Within several months, networks largely rebounded, with 4-clique motifs (M3) indicating reliance on tight cliques for support. Under normalized restrictions (2021–2022), a hybrid structure of “high clustering–long path” emerged, combining offline recovery with persistent digital ties. Post-pandemic (2023–2024), networks became more fragmented, though M3 motifs persisted, suggesting durable reorganization. Behavioral orderliness followed a parallel trajectory: rapid decline in 2020, partial recovery in 2021–2022, and convergence at higher levels after reopening. Students within high-frequency dyads displayed greater orderliness, underscoring a potential bidirectional relationship between stable ties and routine. These findings highlight the fragility, adaptability, and reconstructive capacity of student social systems, offering data-driven evidence for designing resilience strategies in higher education under future crises.

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1 Introduction

Educational research is undergoing a paradigm shift from small-scale surveys and experiments to data-intensive approaches enabled by ubiquitous digital traces (Peña-Ayala and Cárdenas 2014; Sapiezynski et al. 2017), opening new avenues for systematically capturing complex student behaviors. With the integration of information technologies, such as mobile devices (Wu et al. 2019), online learning platforms (Zhu et al. 2021), and campus WiFi systems (Zhukov et al. 2018), large-scale datasets reflecting students’ interactions are increasingly accessible. These data sources allow researchers to uncover latent behavioral patterns that are difficult to capture using conventional self-reported or sparse observations (Brinton and Chiang 2015).

Network science provides a powerful analytical framework for modeling and visualizing such complex systems (Caldarelli 2007), with applications spanning scientific collaboration (Xiao et al. 2024), finance (Bardoscia et al. 2017), and social systems (Derbogossian et al. 2025). Within education, social network analysis (SNA) has been employed to examine peer relationships and interaction dynamics (Veldman et al. 2025; Zhou et al. 2025; Wang and Shang 2024), linking network structures to academic and psychological outcomes. However, methodological challenges remain: many studies rely on survey-based or retrospective designs subject to selection bias and data latency, or focus on isolated behavioral variables (Supke et al. 2024; Brown et al. 2024; Guillot et al. 2024; Chen and Lim 2024; Rotvold et al. 2024). These limitations narrow our understanding of how multiple behavioral dimensions co-evolve in real time, especially during periods of systemic disruption.

The COVID-19 pandemic serves as a natural experiment, profoundly reshaping students’ social lives. Previous studies have primarily investigated psychological effects, including anxiety, depression, and self-efficacy (Heumann et al. 2024; Gracia-Liso et al. 2024; Shahrababaki et al. 2024), along with shifts in lifestyle behaviors such as dietary habits, physical activity, and media consumption (Dziewior et al. 2024; Kanberger et al. 2025; Wright et al. 2024; Haug et al. 2024), and have also addressed broader aspects of well-being (Rotvold et al. 2024). While valuable, these studies often overlook the structural configurations of student social interaction networks and how they dynamically responded to containment measures. As recent work indicates, the pandemic affected not only individual wellbeing but also the organization of social relationships and patterns of connectivity (Chen 2024). Addressing this gap requires a network-level perspective. Against this backdrop, we adopt SNA to investigate the evolution of campus friendship networks throughout pre-pandemic, mid-pandemic, and post-pandemic phases. Guided by established frameworks (Yang et al. 2020), we utilized dining-hall co-occurrence data from over 30,000 university students to reconstruct temporal friendship networks. Using motif detection, node centrality, and temporal regularity indices, we characterize both global structural properties and local behavioral dynamics.

Our contributions are as follows:

1. We constructed a 44-month longitudinal dataset capturing campus friendship interactions across eleven semesters, spanning pre-, mid-, and post-pandemic stages.
2. Temporal network analysis revealed significant stage-dependent shifts in topology, with connectivity and clustering coefficients showing nonlinear responses, including sharp post-pandemic rebound effects.
3. Motif analysis uncovered the increased presence of cohesive four-node subgraphs during and after lockdown, indicating structural reorganization toward denser clusters.
4. Behavioral regularity indices derived from dining data demonstrated marked disruptions during lockdown and recovery thereafter, with triadic friendship groups exhibiting notably synchronized routines.

The remainder of this paper is structured as follows: Section 2 reviews related literature; Section 3 describes the data and methodology; Section 4 presents empirical

results with discussion; and Sections 5 conclude with limitations and future research directions.

2 Literature review

2.1 Social network analysis in education

SNA provides a powerful theoretical and computational framework for analyzing interactions in complex social systems (Zhang and Wang 2022). By conceptualizing individuals as nodes and their interactions as edges, SNA shifts the research focus from isolated behaviors to interdependent relational structures (Kaba et al. 2023). Core metrics such as degree, density, and centrality offer systematic ways to assess individual influence, group cohesion, and overall network efficiency (Giri et al. 2014). This relational perspective enables researchers to capture dynamic peer effects, complementing traditional reliance on individual-level indicators such as grades or attendance (Lee and Bonk 2016).

SNA is particularly relevant to educational contexts, where peer influence significantly shapes students’ learning and development (Harris 1995). Empirical findings consistently highlight that friendships often evolve into study partnerships, facilitating knowledge sharing and collaborative learning (Tang et al. 2011; Cao et al. 2024). For instance, Kassarnig et al. (2018) used smartphone data to show that network structures predicted academic performance more effectively than conventional demographic or personality measures. Similarly, Thulasidas et al. (2023) demonstrated that students in online mathematics courses preferentially sought help within their established communities, highlighting the importance of cohesive subgroups. These findings align with broader evidence that academic success emerges not only from individual motivation but also from collective structures of influence and support, echoing recent work on academic performance predictors in large student populations (Bhutta et al. 2025; Rożman et al. 2025).

Despite its strengths, SNA faces methodological challenges. Not all systems exhibit explicit relational structures, and available data often fail to capture latent or informal ties (Battiston et al. 2020). To address these limitations, researchers have developed techniques to infer social connections from digital traces. Examples include RFID-based detection of physical proximity among undergraduates (Liu et al. 2017), log-based reconstruction of online learning communities (Wang and Jiang 2024), and comment-derived interactions in political debates (Gasa et al. 2024). These approaches leverage social theories such as structural balance and structural holes (Tang et al. 2012), extending SNA to contexts where relationships are implicit.

Beyond general network analysis, motif detection enhances understanding of structural micro-patterns. Motifs—recurrent subgraph structures—reveal local organizational principles otherwise obscured in global metrics (Faizi et al. 2020). Although originally applied to biological networks (Yu et al. 2019), motif-based approaches are increasingly relevant in social systems. Recent studies have used motifs to examine international alliances (Mastrandrea et al. 2024), to trace pathways of information diffusion (Yang et al. 2023), and to capture emotional exchanges in online crisis communication (Kušen and Strembeck 2021). In education, motif analysis provides a nuanced method to

uncover community formation, peer triads, and functional clusters within learning environments.

2.2 COVID-19 and individual behavioral shifts

The COVID-19 outbreak in early 2020 created an unprecedented disruption to education systems worldwide. In China, the policy of “suspending classes without halting learning” marked a rapid nationwide transition to digital instruction (Zhang et al. 2020; Ministry of Education of China 2020). Similar interventions occurred globally, motivating extensive research into the impacts of online and hybrid learning on student experiences.

Studies reveal that the shift to online learning produced complex effects on students’ academic outcomes, psychological wellbeing, and behavioral patterns. For example, Zeng and Luo (2021) showed that students’ mathematics and English performance declined significantly during online learning, consistent with findings that prior achievement remained the strongest predictor of resilience to disruption. Fomina et al. (2021) and Liu et al. (2020) highlighted heightened psychological stress among undergraduates, particularly among those facing uncertainty about future prospects. At the same time, some research reported minor or temporary effects: Hölbl et al. (2022) found that course-related perceptions gradually stabilized after initial disruption. More recent studies also demonstrate that motivation, mental health, self-efficacy, and social support strongly mediated pandemic learning outcomes, reaffirming the multidimensional nature of academic performance (Bordbar et al. 2025).

Methodologically, much of this literature relies on self-reports or cross-sectional surveys, limiting real-time monitoring or generalizability. Big data approaches have thus emerged to mitigate these shortcomings. For instance, Shi (2023) analyzed daily digital learning traces from over 170 school districts in the U.S., finding that engagement declined despite longer online study durations, and disparities widened across racial and socioeconomic groups. Similarly, Manir and Deshpande (2023) and Mohammed et al. (2021) employed computational models such as random forests, clustering, and regression to predict pandemic effects on GPA and achievement. Abe and Cheng (2024) extended this line of inquiry by constructing predictive models based on learning analytics, underscoring the potential of machine learning to capture hidden behavioral patterns.

In summary, these studies underscore two critical themes: (i) pandemic-induced disruptions simultaneously affected students’ performance, psychology, and social interactions, often in uneven ways; and (ii) emerging data-driven methods such as SNA and motif-based analytics can reveal dynamic patterns overlooked by traditional survey-based designs. Our study builds upon this foundation by applying temporal network analysis and motif analysis to campus friendship networks spanning pre-, mid-, and post-pandemic stages, thereby integrating behavioral, structural, and temporal perspectives into a unified analytic framework.

3 Materials and methods

3.1 Data description

This study investigates the longitudinal behavioral patterns of undergraduates through campus smart-card transaction records. Between January 2019 and July 2024, we collected 65 million entries containing anonymized student identifiers, transaction times, locations, and amounts. Canteen dining behaviors serve as the primary proxy for daily interactions, as each transaction precisely records dining location and time. To ensure data reliability, students with fewer than ten monthly transactions were excluded.

The university maintains eight canteens and 167 service windows, from which we obtained 496,955 sequential transaction records suitable for sequence analysis. For the network construction, 63,131,695 valid canteen transactions across 11 semesters were compiled (Table 1). Student identifiers were irreversibly encrypted through hashing to safeguard privacy.

Table 1: Canteen data from 2019 to 2024.

Months	Average Transaction Records	Average Valid Students
2019.03–2019.06	1 926 134	30 073
2019.09–2019.12	2 034 531	30 491
2020.03–2020.06	21 199	548
2020.09–2020.12	2 186 417	31 297
2021.03–2021.06	2 075 645	30 914
2021.09–2021.12	1 325 772	26 500
2022.03–2022.06	861 594	20 500
2022.09–2022.12	942 623	20 631
2023.03–2023.06	809 171	19 113
2023.09–2023.12	833 434	16 733
2024.03–2024.06	717 522	16 701

3.2 Inferring social relationships

We construct a friendship network under the behavioral assumption that friends are statistically more likely to dine together—i.e., to co-occur at the same cafeteria and within the same time window—compared to strangers. This approach follows the co-occurrence methodology proposed by [Yang et al. \(2020\)](#). Formally, a tie is established if the observed co-dining frequency between two individuals significantly exceeds the baseline chance expectation. This method captures latent social affinity from behavioral traces while mitigating spurious correlations due to random overlaps.

3.3 Network analytical methodologies

The inferred social network is represented as an undirected graph $G(V, E)$, where $V = \{v_1, v_2, \dots, v_n\}$ denotes the set of students (nodes) and E the set of friendship

ties (edges). Standard network statistics were used to evaluate structural configuration (Table 2), including local clustering tendencies (clustering coefficient), randomness vs. order (network entropy, Shannon formulation), degree correlations (assortativity), and global efficiency (average shortest path length(ASPL) and diameter). These measures are frequently employed in educational and mobility network research to assess compactness, reachability, and structural resilience (Bhutta et al. 2025; Bordbar et al. 2025).

Table 2: Network indicator description.

Indicator	Equation	Description
Network diameter	$D = \max_{i,j} d(v_i, v_j)$	D is the length of the longest shortest path among all node pairs, i.e., the maximum geodesic distance in the network.
Network density	$\rho = \frac{2m}{n(n-1)}$	ρ is the ratio of actual connections m to possible connections among n nodes.
Network entropy	$H = -\sum_k p(k) \log p(k)$	H measures the heterogeneity of the degree distribution, where $p(k)$ is the probability of a node having degree k .
Clustering coefficient	$C_i = \frac{2E_i}{k_i(k_i-1)}$	C_i measures the degree of clustering of node i , where E_i is the number of actual links among its k_i neighbors.
Assortativity	$r = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2}$	r measures the tendency of nodes to connect to others of similar degree, where e_{jk} is the joint probability of a degree- j and degree- k connection, and q_k is the degree distribution.
Average degree	$\langle k \rangle = \frac{2m}{n}$	$\langle k \rangle$ is the mean degree of nodes in the network, with m edges and n nodes.
Average path length	$L = \frac{\sum_{i,j} d(v_i, v_j)}{n(n-1)}$	L is the average distance between all pairs of nodes, where $d(v_i, v_j)$ is the shortest path between node i and node j .

3.4 Motif detection

Beyond global indicators, we analyze mesoscopic structural features via network motifs—recurrent subgraph configurations hypothesized to serve as building blocks of complex networks (Stone et al. 2019). For undirected friendship networks, six representative motifs are examined (Fig. 1): chain (M1), clique (M2), 4-clique (M3), star (M4), circle (M5), and tailed triangle (M6). Each captures distinctive behavioral archetypes such as informal dyadic chains, tightly-knit peer groups, or core-periphery hierarchies.

Motif frequency is compared against randomized null models using the algorithm of Pană and Nicolin-Żaczek (2023). Statistical significance is assessed via Z -scores and p -values, consistent with methods applied in social and technological networks (Liu et al. 2022). Overrepresentation of the triangle motif (M2) indicates strong local cohesion, whereas prevalence of star motifs (M4) suggests central hubs in otherwise decentralized structures. Such motif-driven analysis connects macro-level structural indices (e.g., ASPL, diameter) with micro-level interaction patterns, offering insights into how student groups reorganize under perturbations.

3-Node and 4-Node Undirected Graph Motifs

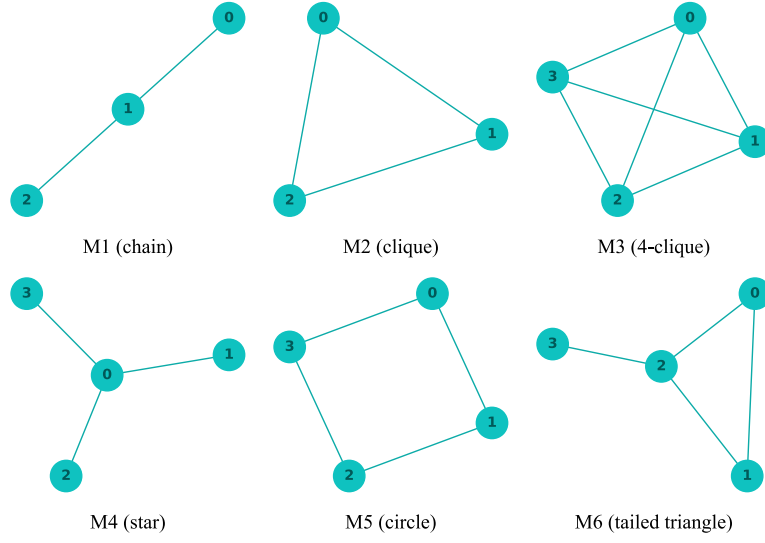


Fig. 1 Representative three- and four-node undirected motifs examined in this study.

3.5 Orderliness of behavioral sequences

In order to quantify temporal regularity in student routines, we employ the actual entropy method (Yang et al. 2020). For each student, the entropy of their dining time-series S_n is computed, with an orderliness index defined as $O_n = -S_n$. Lower entropy corresponds to greater behavioral consistency (e.g., fixed dining times), while higher entropy indicates stochastic or irregular behavior. This measure enables comparison of behavioral regulation across pre-pandemic, pandemic, and post-pandemic stages, linking individual-level orderliness with collective network coherence.

4 Results and discussion

4.1 Network analysis

To systematically reveal the macro-level characteristics and temporal evolution of campus friendship networks, we analyzed 44 networks constructed over 11 academic semesters, based on multiple dimensions including network scale, connectivity, and node centrality. For ease of reference, semesters are encoded as follows: March–June corresponds to the spring semester (denoted as S), and September–December to the fall semester (denoted as F). Accordingly, the identifiers for the 11 semesters are presented in Table 3. Based on this temporal coding, the study was segmented into three broad phases—pre-pandemic (19S–19F), mid-pandemic (20S–22F), and post-pandemic (23S–24S)—to facilitate comparative analysis of structural changes over time.

Table 3: Correspondence between study periods and semester codes.

Phase	Semester Code	Corresponding Time Period
Pre-pandemic	19S	2019.03–2019.06
	19F	2019.09–2019.12
Mid-pandemic	20S	2020.03–2020.06
	20F	2020.09–2020.12
	21S	2021.03–2021.06
	21F	2021.09–2021.12
	22S	2022.03–2022.06
	22F	2022.09–2022.12
Post-pandemic	23S	2023.03–2023.06
	23F	2023.09–2023.12
	24S	2024.03–2024.06

4.1.1 Evolution of network scale

A longitudinal examination of the campus social networks from 2019 to 2024 (Fig. 2) identifies several distinct phases. During the pre-pandemic period, network structures exhibited high integrity, characterized by strong student coverage, a stable and dominant GCC, and only a small fraction of isolated individuals. This reflects the robustness and integrative nature of campus social networks under normal teaching conditions.

In contrast, under the prolonged conditions of pandemic control, systematic structural shifts emerged. First, overall network coverage decreased substantially, indicating a widespread weakening of social ties, particularly affecting peripheral and low-frequency interactions. This suggests that weak ties are more prone to dissolution under sustained external stress, thereby reducing network permeability. Second, network connectivity revealed marked fragmentation. Previously cohesive structures rapidly decomposed into numerous smaller connected components, often organized into secondary subgroups. This structural disintegration eroded the dominance of large-scale connected clusters and significantly diminished network integration and efficiency of information diffusion. Finally, although the core was impacted, it remained relatively stable. The GCC accounted for a smaller proportion of the network, but its internal size, tie strength, and density remained largely unchanged, underscoring the resilience of core groups in maintaining cohesion under systemic fragmentation.

During the post-pandemic stage, even after the resumption of in-person learning and daily activities, the overall scale of friendship networks remained at a relatively low level, without evidence of substantial recovery. This trend indicates that the pandemic shock was not a short-term disturbance but imposed lasting structural changes on students' social relationships. Specifically, the size of the GCC continued to contract, and the pre-pandemic level of integrative centralization was not restored. Instead, the network evolved into a pattern characterized by multiple smaller clusters, reflecting increased structural decentralization. This persistent fragmentation highlights the

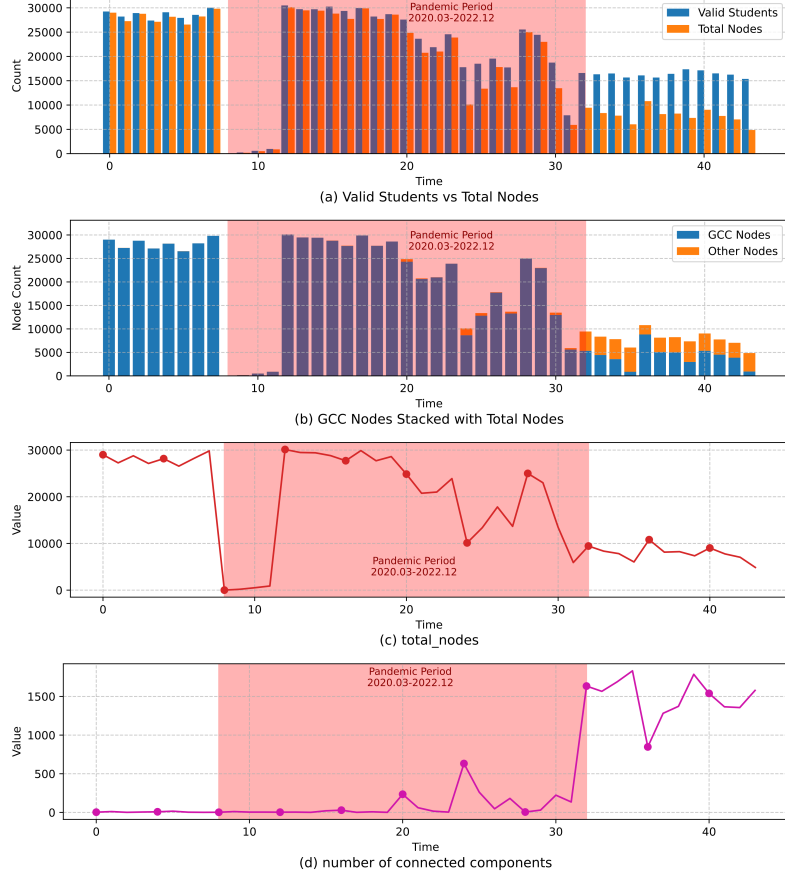


Fig. 2 Temporal evolution of network topological characteristics across semesters. (a) Comparison between average node count and valid students; (b) GCC size distribution; (c) Node count variation; (d) Connected component dynamics.

long-term weakening of cohesion and integrative capacity in campus social networks, even after external restrictions were lifted.

The results of topological measures of GCCs in various phases are statistically listed in Table 4. Results reveal heterogeneous temporal trends across indicators. Network entropy showed highly significant differences across all pairwise comparisons ($p < 0.0001$), with the largest effect size, demonstrating its strong sensitivity to structural dynamics. The clustering coefficient also differed significantly ($p \approx 0.001$), particularly between pre-post and mid-post comparisons, indicating a sustained decline in local cohesiveness. Average degree was consistently significant across all stages ($p < 0.001$), reflecting a systematic reduction in overall connectivity under pandemic conditions. Moreover, average path length and network diameter both increased significantly ($p < 0.001$), suggesting that social networks became less compact and more dispersed in structural terms. By contrast, neither assortativity coefficient nor network density

exhibited significant changes (both $p > 0.05$), and given their limited comparative validity and negligible effect sizes, they were excluded from further analysis.

Table 4: Hypothesis testing results for network metrics.

Metric	Normality (Pre/Mid/Post)	Homosced (Y/N)	Test (p-value)	Significant Groups	Max Effect Size	Adopted (Y/N)
Clustering coefficient	✓/×/×	Y	0.0011	Pre-Post Mid-Post	0.812	Y
Network entropy	✓/×/×	N	0.0001	Pre-Mid Pre-Post Mid-Post	0.958	Y
Assortativity	✓/✓/✓	Y	0.2176	N/A	N/A	N
Average degree	✓/×/×	Y	0.0004	Pre-Mid Pre-Post Mid-Post	0.854	Y
Network density	✓/×/×	Y	0.5833	N/A	N/A	N
Average path length	✓/✓/✓	Y	0.0000	Mid-Post Post-Pre	1.000	Y
Network diameter	✓/×/✓	Y	0.0000	Pre-Post Mid-Post	1.000	Y

4.1.2 Evolution of local clustering

The average clustering coefficient (ACC) is a key metric used to quantify local cohesiveness in social networks. It is calculated as the mean clustering coefficient of all nodes, with values ranging from 0 to 1. A higher ACC indicates that a node’s neighbors are more densely interconnected, approaching a completely connected state, thus reflecting stronger local clustering. Conversely, a lower ACC suggests a looser and more fragmented mesoscale structure.

As shown in Table 5, the time-series statistics of the average clustering coefficient (ACC) reveal marked stage-dependent variation. From the pre-pandemic to the mid-pandemic phase (Pre → Mid), the ACC increased only slightly (0.13 ± 0.03 vs. 0.14 ± 0.04 , +3.3%), suggesting overall stability in local connectivity despite external disruption. However, in the post-pandemic phase the ACC rose sharply to 0.19 ± 0.04 , representing an increase of 36.9% compared with the mid-pandemic level.

The temporal evolution of ACC (Fig. 3) shows values mainly distributed between 0.1 and 0.3, with evident cyclical oscillations. In some semesters (e.g., 19F, 21S, 21F), the curve followed a “decline–rebound–decline” pattern, reflecting the influence of semester-based social rhythms. A striking anomaly was observed in the outbreak semester (Spring 2020), when the largest connected component included only two nodes with a single edge, yielding an ACC of zero. This outlier was excluded from interpretation. A temporary increase appeared during the early containment phase (20S–20F), likely driven by small but stable clusters formed under restricted offline contact conditions, which enhanced local density.

In the post-pandemic semesters, particularly across three consecutive terms (23S, 23F, 24S), the ACC remained consistently higher than pandemic values and stabilized without returning to its pre-pandemic baseline. The highest peak occurred in Fall 2023 (23F), with an ACC of 0.2988, significantly above the contemporaneous average.

This peak coincided with several large-scale campus events, such as the beginning-of-semester activities and the university anniversary celebration, which likely amplified intergroup interactions and temporarily boosted local clustering.

Table 5: Temporal statistics of clustering coefficients ($M \pm SD$, $\Delta\%$).

Period	Mean	Standard Deviation	Δ (%)
Pre	0.13	0.03	—
Mid	0.14	0.04	3.3
Post	0.19	0.04	36.9

Note: $M \pm SD$ represents Mean $\pm$ Standard Deviation; $\Delta\%$ indicates percentage change compared with the previous period.

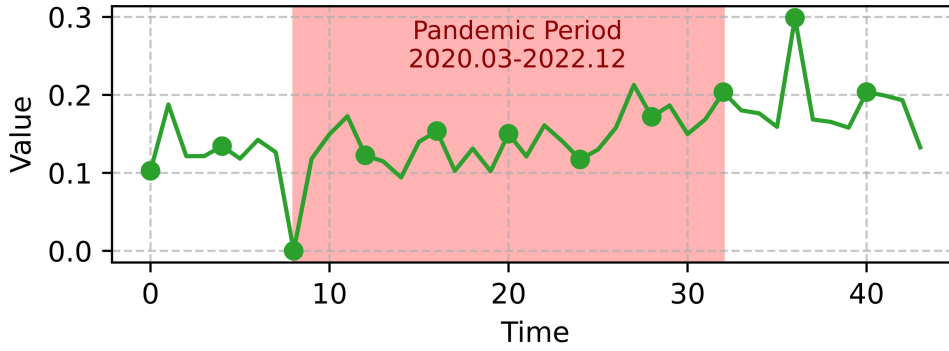


Fig. 3 Temporal evolution of average clustering coefficients.

4.1.3 Evolution of network entropy

Network entropy, an important measure of structural complexity and randomness, demonstrated significant temporal fluctuations and stage-dependent features across the 44 observed networks (Fig. 4).

During the outbreak semester (Spring 2020), the entropy value plummeted to 1.69, reflecting rapid contraction of the network and a sharp reduction in structural complexity under strict control measures. This suggests that stringent restrictions on offline interactions disrupted previously diverse relational patterns, forcing networks into a highly simplified state. Subsequently, during the prolonged pandemic phase (Fall 2021 to Fall 2022), entropy gradually recovered and stabilized, indicating that student social systems adapted by developing new modes of interaction, achieving self-organization under external constraints.

Of particular note is the monotonous decline from Fall 2022 onward, which persisted across four consecutive semesters. By the post-pandemic era (2023–2024), entropy values stabilized at markedly lower levels compared to pre-pandemic fluctuations. This sustained decrease suggests an evolutionary shift toward greater orderliness and predictability in social interactions once restrictions were lifted. Unlike the pre-pandemic entropy patterns, which were characterized by variability, the post-pandemic networks evolved into more stable and less random structures.

This trend can be contextualized with real-world factors. First, post-pandemic social relations exhibited higher stability and more fixed clustering, thereby reducing randomness. Second, certain online communication practices, developed during the pandemic, persisted afterwards, limiting the restoration of weak offline links. Finally, existing studies have documented the pandemic’s lasting psychological and behavioral effects on university students, making them more inclined to maintain a small number of stable ties rather than cultivate wide-ranging, weak social links (Wang et al. 2022).

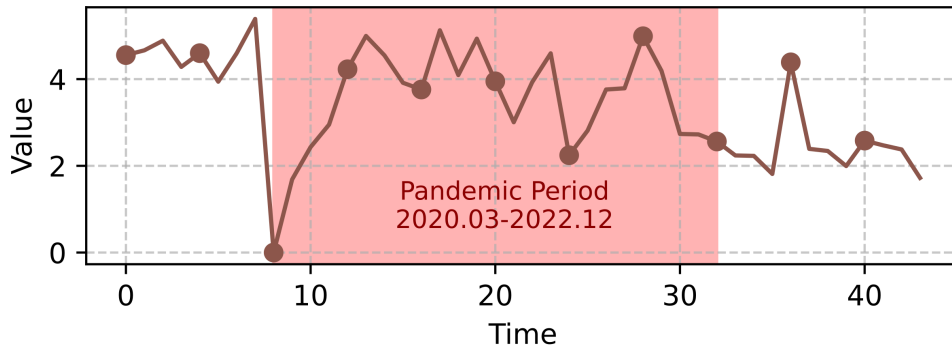


Fig. 4 Temporal evolution of network entropy.

4.1.4 Evolution of network density

Average degree, as a core indicator of connectivity in undirected networks, provides an intuitive measure of social network density. A temporal analysis of average degree across 44 friendship networks (Fig. 5) revealed substantial heterogeneity, with values ranging from 1.00 to 82.65.

As shown in Fig. 5, average degree exhibited distinct stage-dependent trends. During the pre-pandemic and early pandemic phases, values fluctuated markedly, with a range close to 60. Such volatility suggests that prior to the pandemic, student networks could embody both highly dense structures with large-scale interactions as well as low-density structures due to contraction of certain subnetworks. Entering the mid-pandemic phase, the mean degree declined significantly, dropping from 41.86 in the pre-pandemic stage to 22.53 in mid-pandemic, a reduction of approximately 46.2%.

Variations also narrowed, reflecting the restricted campus environment and reduced frequency of face-to-face interactions.

In the late-pandemic and post-pandemic periods, the decline persisted. Most values fell below 10, with the overall mean dropping further to 8.63, representing an additional decrease of 61.7% from the mid-pandemic level. This sustained contraction indicates that even after restrictions were lifted, student social networks did not return to pre-pandemic levels of density. Instead, they stabilized at a markedly lower connectivity state. In essence, although institutional measures were gradually relaxed, actual patterns of student interaction became sparser and more homogenized. Our results are consistent with recent observations that social networks, after pandemic shocks, evolve toward reduced complexity and stabilized structures (Zhang and Tang 2025; Fang et al. 2022). These findings suggest that the pandemic not only reshaped immediate levels of network density but also generated enduring impacts on the scale and organization of long-term social interactions.

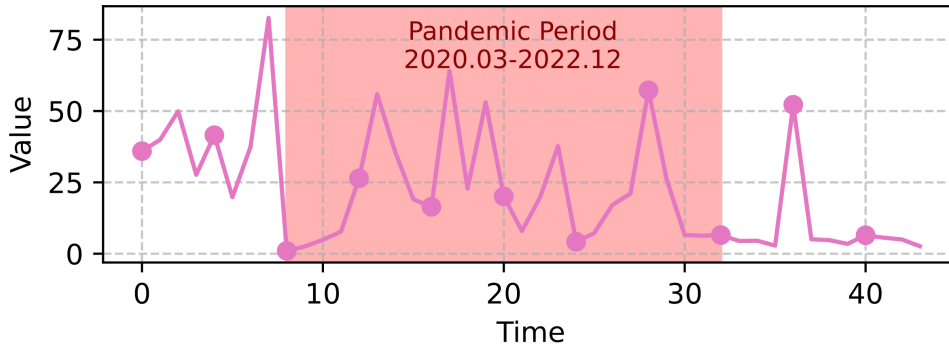


Fig. 5 Temporal evolution of average degree.

4.1.5 Evolution of path characteristics

Average shortest path length (ASPL) and network diameter are fundamental indicators of network topology, reflecting the compactness of interactions and the scale of structural reach. Correlation analysis revealed a strong positive association between the two measures (Pearson $r = 0.97$, $P = 2 \times 10^{-26}$), with the regression equation $y = 3.28x - 2.25$ ($R^2 = 0.93$). This high degree of fit suggests that the two metrics evolve in close synchrony and can be jointly considered in representing network expansion and sparsification.

From a temporal perspective, both metrics remained relatively stable during the pre-pandemic stage (Fig. 6). However, in the pandemic years (March 2020–December 2022), distinct fluctuations emerged. Specifically, ASPL displayed a non-linear pattern of increase followed by decline, whereas diameter exhibited larger variation, reflecting possible structural adjustments in which the longest paths between individuals were

first extended and later compressed as a result of containment policies. This stage-specific oscillation indicates that pandemic impacts on connectivity extended beyond local clustering to affect global structural topologies, leading to periodic stretching and contraction of network paths.

In the post-pandemic stage (2023 onward), both ASPL and diameter increased substantially, with diameter showing particularly pronounced growth. Compared with pandemic levels, average values more than doubled (approximately +115.8%), and ASPL also lengthened significantly. This expansion suggests that post-pandemic networks became less compact, with longer paths between nodes and weaker global coherence. Consistent with findings from broader social network studies, such trends may reflect processes of social reorganization, where previously dense, localized clusters are gradually replaced by more diffuse, cross-group ties (Steijvers et al. 2022).

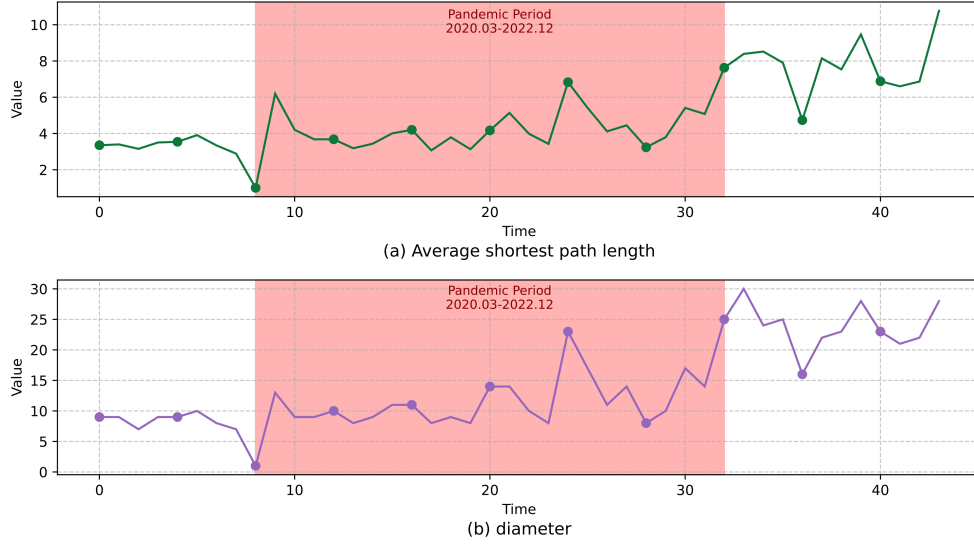


Fig. 6 Temporal evolution of path characteristics in student social networks. (a) Average shortest path length (ASPL) variation across semesters; (b) Network diameter chronological changes.

4.1.6 Evolution of connection preferences

Assortativity serves as an important indicator of connection preferences in a network, capturing the extent to which nodes preferentially connect with similar others. Across the 44 temporally ordered friendship networks, assortativity coefficients exhibited substantial dynamic variation (Fig. 7). Overall, the coefficients fluctuated between -0.06 and 0.46, with a mean of 0.21 ($SD = 0.12$). In the vast majority of observed intervals (approximately 95.5%), values were positive ($r > 0$) and significantly higher than those expected in random networks ($p < 0.01$). This indicates a pervasive preference for homophily, i.e., similarity breeds connection, within student social networks.

Nevertheless, this tendency was not entirely stable. At the onset of the pandemic (Semester 20S), the assortativity coefficient briefly turned negative, reflecting transient disassortative patterns. This anomaly aligns with the sudden environmental disruption during this period: on the one hand, the abrupt transition to remote teaching may have weakened the stability of existing peer circles and encouraged cross-group, heterogeneous interactions; on the other hand, specific academic support behaviors, such as senior students assisting junior cohorts, may have facilitated connections between otherwise dissimilar individuals. As the pandemic progressed into mid-to-late stages, assortativity values returned to positive levels and demonstrated stability, suggesting that student networks gradually reestablished their dominant homophilous patterns under the adjusted social environment.

Assortativity temporal evolution reveals both the disruptive and adaptive effects of external shocks. The short-term emergence of disassortativity exemplifies pandemic-driven restructuring of cross-group linkages, while the long-term trend underscores the persistence of homophily as a structural preference. This observation is consistent with established findings on friendship networks in educational contexts, which emphasize inequality, homophily, and cultural embeddedness (An 2022), as well as broader theoretical insights that homophily is a fundamental organizing principle in social networks (Fu et al. 2012).

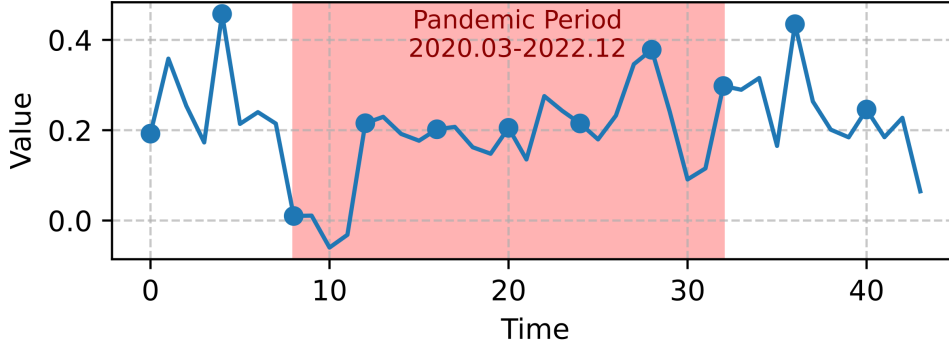


Fig. 7 Temporal evolution of assortativity coefficient.

4.2 Motif analysis

To further examine behavioral shifts in student social interactions across the 44 friendship networks, motif analysis was employed to capture micro-level structural features. Motifs, defined as small recurring subgraph patterns, represent the fundamental building blocks of networks and embody key relational functions such as information flow, group cohesion, and role differentiation (Felmlee et al. 2021; Cakmak et al. 2022). Each of the 44 networks was compared against 1,000 randomized counterparts per observation, with statistically overrepresented motifs identified at $p \leq 0.01$. Z-scores

were log-transformed to mitigate distributional differences, and the resulting motif set is summarized in Table 6 and Fig. 8.

The temporal evolution revealed clear stage-specific patterns. Triadic closures (M2) remained consistently significant before, during, and after the pandemic, underscoring the robustness of tightly knit three-person clusters in student friendship structures. By contrast, M3 displayed the most dynamic variation: emerging during the pandemic onset (Spring 2020), appearing intermittently in the mid stage, and then escalating sharply in the post-pandemic years. In 10 of the 12 post-pandemic observations, M3 achieved significance, often with Z-scores exceeding 7.0, indicating that the pandemic catalyzed the consolidation of stable four-person groups whose prominence persisted and intensified thereafter. Other motifs exhibited more muted dynamics: cyclic ties (M5) were consistently present but at lower Z-scores, reflecting weaker though common cohesion patterns; while peripheral-attachment motifs (M6) declined steadily, with an average pre-pandemic Z-score of 4.66 ± 0.20 falling to approximately 3.40 ± 0.35 post-pandemic, suggesting that open triad-centered structures lost ground to closed cliques as dominant organizing forms. In contrast, motifs representing extended chains (M1) or hub-and-spoke structures (M4) never reached significance at any stage, indicating that student networks favored locally reciprocal clusters over centralized hubs or weak, linear connections.

The temporal evolution analysis confirmed a stable ordering across all stages— $Z(M2) > Z(M6) > Z(M5)$ —highlighting the enduring dominance of triangular closures. Most striking, however, was the post-pandemic amplification of M3, which reflects a pronounced shift toward small-group consolidation in response to systemic shocks. This pattern resonates with recent evidence that local motif structures act as sensitive indicators of perturbations in social systems, especially under crisis conditions (Shridhar et al. 2025). Collectively, these results suggest that the pandemic not only reinforced cohesive motifs such as triadic closures and stable four-person groups but also diminished the relative importance of connector-type motifs, leaving a durable imprint on the micro-scale architecture of student social networks.

Table 6: Significant network motifs identification.

Motif	Pre (n=8)			Mid (n=24)			Post (n=12)		
	Count	Z_{Mean}	Z_{SD}	Count	Z_{Mean}	Z_{SD}	Count	Z_{Mean}	Z_{SD}
M1	–	–	–	–	–	–	–	–	–
M2	8	5.35	0.18	23	4.99	1.06	11	4.62	0.56
M3	–	–	–	5	6.21	1.89	10	7.29	0.80
M4	–	–	–	–	–	–	–	–	–
M5	8	3.08	0.87	20	2.80	0.62	10	3.01	0.79
M6	8	4.66	0.20	23	4.32	0.98	11	3.40	0.35

Note: Z_{Mean} represents mean z-score; Z_{SD} indicates standard deviation of z-scores. Dashes (–) indicate non-significant motifs.

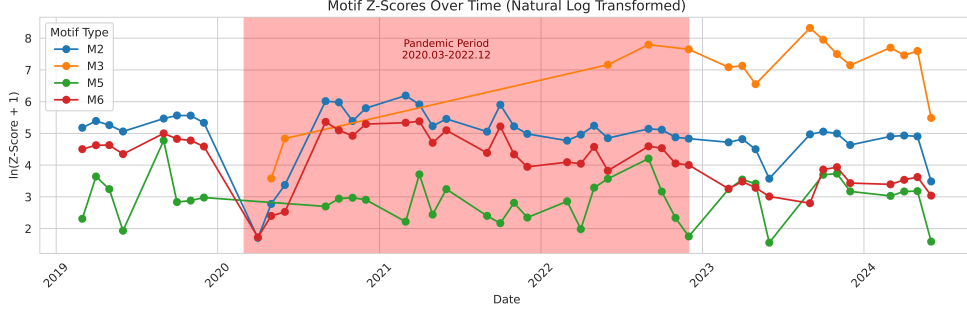


Fig. 8 Temporal evolution of network motif Z-score.

4.3 Orderliness analysis

Orderliness is an important indicator for measuring the regularity of students' daily routines, with its value directly reflecting the degree of behavioral stability. To systematically examine the impact of the COVID-19 pandemic on student social behavior, this study selects representative months from different stages of the pandemic for comparative analysis. Specifically, we include: June 2019 (baseline, pre-pandemic), June 2020 (early outbreak/emergency), June 2021 and June 2022 (normalized control, long-term impact), and June 2023 and June 2024 (post-pandemic period). June serves as an ideal observation window since it corresponds to the semester's end without major holiday interruptions, ensuring relative network stability.

Two steps are employed in this section:

1. **Identification of high-frequency dyads:** For each month, node pairs forming part of motif M2 (triadic closure, i.e., triangle structure) are identified. Their weights are defined as the cumulative frequency of co-occurrence, with the top 10 ranked dyads selected as the set of *high-frequency social ties*.
2. **Orderliness computation and comparison:** For students participating in these high-frequency ties, their orderliness scores are computed and compared across pandemic stages. Differences are evaluated against random node pairs to determine whether central social actors are more affected by pandemic disruptions.

4.3.1 Identification and analysis of high-frequency dyads

The weight of each dyad corresponds to its co-occurrence frequency across the network, and the top ten dyads per month were retained for analysis (Table 7; Fig. 9 and Fig. 10). Results revealed pronounced stage-dependent fluctuations. In the pre-pandemic year (2019), the mean dyad weight was relatively high (75.5) but accompanied by large variability ($SD = 28.81$), indicating heterogeneous interaction intensities with some groups exhibiting strong cohesion. At the onset of the pandemic in 2020, mean weights dropped sharply to 33.4 (a 56% decline), with reduced variability ($SD = 5.34$). This marks a contraction of triadic interactions under strict mobility restrictions. By contrast, 2021 displayed a striking rebound, with mean weight surging

to 118.1 and extreme outliers up to 200.0 ($SD = 29.63$). These patterns indicate an intensified concentration of activity within a few tightly bonded groups. Under the normalized control of 2022, mean weight declined to 72.9 but variability reduced markedly ($SD = 4.25$), suggesting convergence in group interactions rather than the dominance of a handful of dyads. In the post-pandemic years (2023–2024), mean weights again fell to around 33.8–38.4, similar to 2020 levels, though with slightly higher variability by 2024 ($SD = 9.78$), implying subdued but increasingly differentiated interaction structures.

Distributional analyses offer further insight into these dynamics. Certain dyads consistently appeared among the top-10 across multiple years, reflecting enduring core relationships. The sharp 2021 peak was characterized by highly centralized triads (weights of 200.0, 126.0, and 111.0), whereas the 2022 profile showed convergence in the top three dyads (mean ≈ 78.0), suggesting a temporary homogenization of strong ties. Taken together, these results point to non-linear and stage-dependent effects of the pandemic: an initial contraction in 2020, a phase of exceptional reinforcement of core groups in 2021, and, after 2022, a dispersion toward weaker yet persistent differentiation as networks stabilized without returning to pre-pandemic diversity.

Table 7: Annual June triad closure metrics ($M \pm SD$).

Year	Weight Mean	Weight SD
2019	75.5	28.81
2020	33.4	5.34
2021	118.1	29.63
2022	72.9	4.25
2023	33.8	7.52
2024	38.4	9.78

Note: $M \pm SD$ represents Mean $\pm$ Standard Deviation.

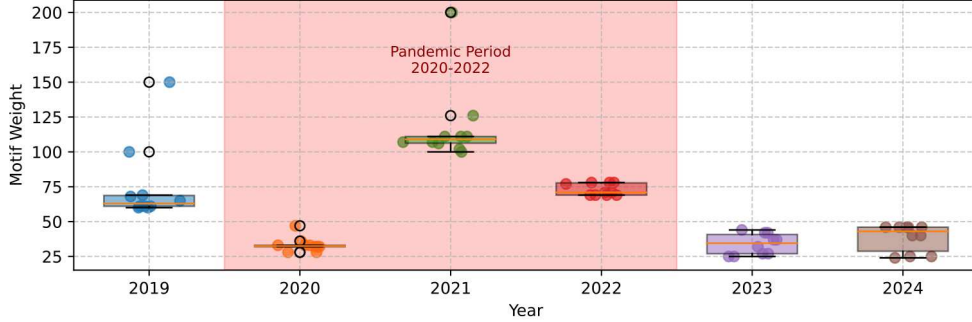


Fig. 9 Comparative distribution of June triad weights.

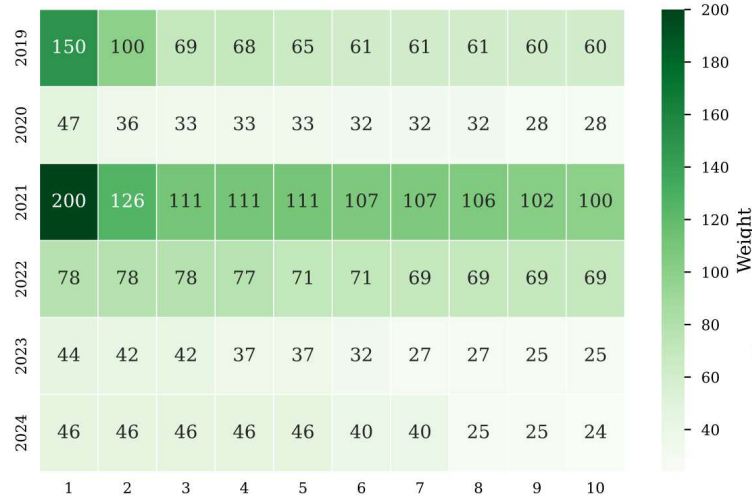


Fig. 10 Heatmap of June triad connection strengths.

4.3.2 Orderliness analysis of high-frequency dyads

We next compared orderliness values among individuals embedded in high-frequency dyads across pandemic stages (Fig. 11, Fig. 12, and Table 8). The temporal evolution revealed distinct patterns. In the pre-pandemic year (2019), the baseline mean orderliness score was 1.52 ($SD = 0.30$, skewness = -0.66), reflecting a generally regular lifestyle. At the onset of the pandemic (2020), mean orderliness dropped sharply to 1.18 (-22.6%), accompanied by heightened variability and a more symmetrical distribution (skewness = -0.08), demonstrating the immediate disruptive impact of lockdown conditions. During 2021–2022, orderliness partially recovered to values between 1.47 and 1.63, and distributions again showed left-skewness (skewness = -0.62 to -0.68), indicating adaptation within institutional routines despite lingering restrictions. By 2023–2024, orderliness peaked at 1.80–1.82, with variability reduced ($SD = 0.23$ – 0.27), suggesting the consolidation of highly regular daily rhythms and lifestyle convergence across individuals.

Further distributional analysis sheds light on group differences and extreme cases. The gap between the top-10% and bottom-10% students widened during the pandemic: from 1.45 (221.6%) in 2019 to a peak of 1.57 (247.9%) in 2021, before narrowing to 1.00 (79.9%) in 2024, reflecting post-pandemic convergence in lifestyle regularity. Outlier behaviors were also notable: in 2022, the lowest observed orderliness score dropped to 0.28, signaling extreme irregularity under prolonged disruptions. These anomalies diminished after 2023, with minimum values rising to 0.86 and outlier prevalence reduced to about 2%, underscoring a broad stabilization of behavioral patterns. A Kruskal–Wallis test confirmed significant differences in orderliness distributions across stages ($p < 0.001$), while low within-group variance (mean = 0.042) indicated increasing behavioral synchronization. These results show that the pandemic reshaped

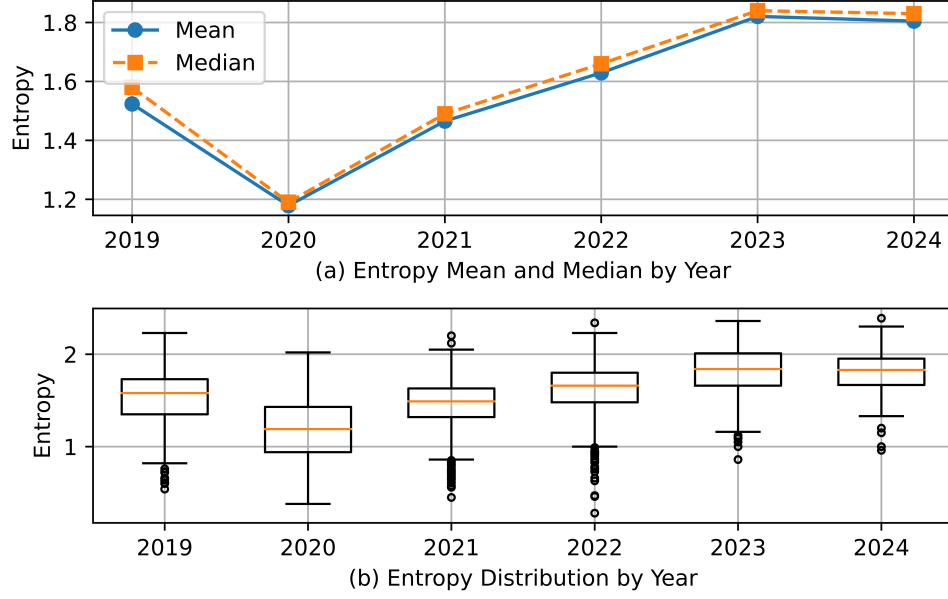


Fig. 11 Temporal dynamics and distribution characteristics of student behavioral orderliness (a) Semester-wise evolution of orderliness index; (b) Boxplot distribution comparison across pandemic phases.

Table 8: Outlier detection in orderliness metrics.

Year	Threshold Interval	Number of Outliers (%)	Maximum	Minimum
2019	[0.78, 2.30]	10(2.3%)	–	0.54
2020	[0.20, 2.17]	(0.0%)	–	–
2021	[0.86, 2.09]	37(2.5%)	2.2	0.45
2022	[1.00, 2.28]	25(1.6%)	2.34	0.28
2023	[1.14, 2.53]	7(2.3%)	–	0.86

orderliness in non-linear stages—a sharp disruption in 2020, partial recovery in 2021–2022, and post-2023 convergence—highlighting both the resilience of core dyads and the structural continuity of student networks even amid persistent social constraints.

5 Conclusion and future directions

5.1 Summary

This study analyzed over 65 million transaction-based interaction records from a Chinese university (2019–2024) to reconstruct temporal friendship networks and examine

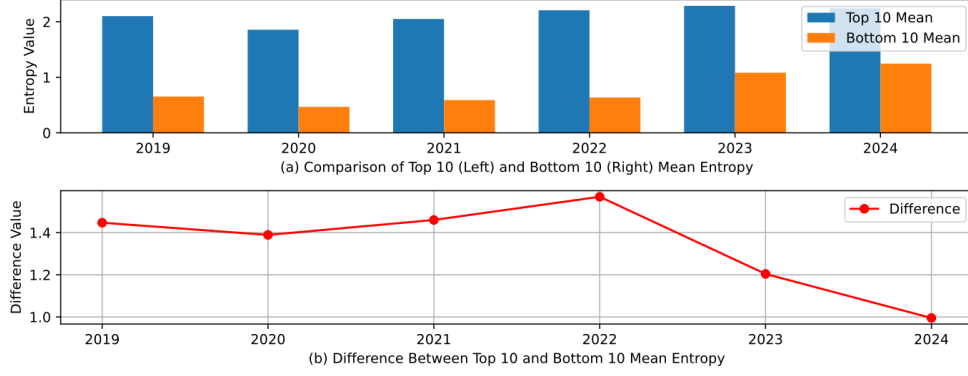


Fig. 12 Orderliness comparison: top/bottom decile students. (a) Comparison of top 10 (Left) and bottom 10 (Right) mean entropy. (b) Difference between top 10 and bottom 10 mean entropy.

behavioral orderliness under the shock of COVID-19. The results reveal several phases of dynamic structural change. First, at the onset of the pandemic in Spring 2020, network indicators such as clustering coefficient, entropy, and average degree declined, reflecting a rapid breakdown of established daily social patterns. Second, within three to four months, a process of crisis adaptation emerged: networks recovered to over 85% of their baseline levels, and the appearance of 4-clique motifs (M3) indicated that students formed tighter groups to sustain social support. Third, during the prolonged restriction period of 2021–2022, the networks stabilized into a mixed topology with high clustering but extended path lengths, reflecting the coexistence of resumed offline relations and digitally mediated ties. Finally, in the post-pandemic era (2023–2024), networks became increasingly fragmented, with the largest connected component losing its dominance, while high-frequency 4-clique motifs remained prevalent—evidence of a durable restructuring of social habits rather than a temporary response.

In parallel, significant shifts in behavioral orderliness were observed. Orderliness declined sharply during the initial outbreak, rebounded during periods of normalized pandemic control, and peaked in the post-pandemic phase, accompanied by reduced group-level disparities. Moreover, students embedded in high-frequency dyads exhibited notably higher orderliness than randomly paired peers, underscoring the strong coupling between structural ties and behavioral regularity. Taken together, these findings indicate that the pandemic not only reduced the overall scale of student interactions in the short term but also produced a profound reorganization of network structures and durable reshaping of daily behavioral routines.

5.2 Implications

Several broader implications can be drawn from this study in dialogue with existing literature. First, the contraction of networks and the strengthened preference for strong ties indicate that students increasingly relied on smaller, core groups. This finding corresponds with prior studies showing that, during the pandemic,

students tended to reduce weak connections while reinforcing stronger peer bonds (Sigurdardottir et al. 2023). Second, the emergence of fragmented and multi-centric network structures in the post-pandemic period, together with the reduced dominance of the largest connected component, suggests that pandemic cohorts (2020–2022) may encounter difficulties in accumulating social capital. This observation resonates with earlier work highlighting potential generational disparities in social capital, with long-term consequences for educational attainment and psychological well-being (Benítez-Andrades et al. 2021). Moreover, the close correspondence between behavioral orderliness and network recovery underscores the coupling of lifestyle regularity with patterns of social engagement. Such evidence extends the literature on psychological-behavioral co-regulation mechanisms under external shocks (Fang et al. 2022). Finally, the study carries practical significance for educational management: post-pandemic “social streamlining” and “social fatigue” highlight the importance of creating structured cross-group activities and fostering diverse interactions to counterbalance fragmentation and safeguard students’ support systems.

Despite these contributions, several limitations remain. First, the inference of friendships from dining-hall co-occurrence, while statistically reasonable, tends to underrepresent weak and spontaneous ties that are less visible in smart-card transaction records. Second, the absence of demographic attributes—such as gender, academic year, or academic discipline—restricts the ability to capture heterogeneous responses across subgroups, leaving unexplored variation in how different populations experienced and recovered from the social disruptions.

5.3 Future directions

Future research can be extended along several promising directions. First, multimodal data integration should be considered. Beyond campus card records, combining complementary sources such as online social media activity, class attendance logs, and mobile sensing data would enable a richer characterization of students’ interaction channels and the interplay between formal and informal networks. Second, group heterogeneity analysis is needed. Incorporating demographic attributes—such as gender, academic year, and academic discipline—can reveal differentiated trajectories of student communities and help identify subgroups more vulnerable to social isolation or disruption effects. Third, methodological advancement offers important potential. Emerging approaches such as graph neural networks, temporal motif analysis, and multilayer dynamic modeling can capture fine-grained temporal changes and the evolution of weak ties with higher fidelity than static or aggregate methods. Finally, longitudinal tracking and outcome coupling should be strengthened. By linking evolving network structures to long-term outcomes—including academic performance and psychological well-being—future studies can clarify how social resilience interacts with individual development. Such evidence would provide both theoretical insight and practical guidance for designing targeted educational interventions in future crises (Smith et al. 2023).

Data availability

The data that support the findings of this study are available from Central China Normal University (CCNU), but restrictions apply to the availability of these data, which were used under licence for the current study and so are not publicly available. The data are, however, available from the authors upon reasonable request and with the permission of CCNU.

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Competing interests

The authors declare no competing interests.

Ethical approval

This study was conducted in accordance with the Declaration of Helsinki and all relevant institutional and national guidelines and regulations. The research protocol was reviewed and approved by the Institutional Review Board of Central China Normal University (Approval No. CCNU-IRB-202501024b) on January 10, 2025. The dataset was provided by the university's Information Technology Office under a formal data use and confidentiality agreement.

Informed consent

The study analyzed existing administrative records that had been fully anonymized by the data holder prior to disclosure; no personally identifiable information was accessible to the researchers. The requirement for individual informed consent was formally waived by the Institutional Review Board of Central China Normal University on the grounds of minimal risk and the use of de-identified data (Waiver/Approval ID: CCNU-IRB-202501024b; Waiver date: 10 Jan. 2025). Accordingly, no consent was sought or obtained.