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A Graph-Theoretical Analysis of Student Friendship Networks Across Senior High School Tracks in a Public School Using Gephi Software

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Abstract: To effectively promote inclusiveness and cooperation in a diverse school setting, it is crucial to grasp the dynamics of friendship formation among students. This study applied the principles of graph theory and social network analysis to investigate the friendship patterns of senior high school students in a school in the City of Malolos. It aimed to describe connection patterns, identify key bridging individuals, and assess the overall cohesiveness of the department's social structure. The study employed peer nomination techniques to gather data from 597 students. The data were analyzed using the Gephi software package. The results of the study showed that every student has, on average, five close ties, resulting in a moderately dense but highly interconnected network. The modularity value of 0.678 revealed strong natural clustering along the academic strands, with inter-strand ties still visible. The centrality analysis revealed students who act as bridging actors to facilitate communication across the groups. The study concludes that the overall network structure is balanced and inclusive despite the divisions along the academic strands.

Keywords: *Graph theory, Gephi, social network analysis, student friendships, senior high school, nodes, edges*

1. INTRODUCTION

The different contexts of friendship networks have been instrumental in understanding the social relationships that shape behavior and learning. Quiroga-Sánchez et al. (2022) established that in highly connected settings, peer influence among adolescents is more visible. In a similar study conducted in the United States, Prochnow et al. (2025) established that students who are centrally located in friendship networks have more influence among their peers. The above studies demonstrate the importance of using graph theory metrics, such as centrality and clustering coefficients, in studying peer relationships and influential individuals in friendship networks.

In the Philippine setting, graph theory has been used as a tool for understanding patterns of social behavior in communities. Gamboa (2023) cited that measures such as average degree, clustering coefficient, and modularity clarify the structure of groups. Faulkner et al. (2021) performed a network analysis on out-of-school youth in Mindanao and investigated communication and collaboration patterns among groups. The results showed the effectiveness of network analysis in identifying structural properties that influence participation and interaction in Filipino social contexts.

Friendships are an important aspect of the educational and individual growth of senior high school students. Edillor et al. (2024) conducted research on Grade 12 students at Bestlink College of the Philippines in an online setup and concluded that communication barriers and self-confidence were factors that influenced the formation of friendships. The research also proved that surveys and peer mapping were useful techniques in exploring how groups of students were formed. While previous research has made valuable contributions to the field, there is a lack of studies specifically utilizing graph theory in the context of classroom friendship structures in Philippine senior high schools. Most of the existing research is centered on the broader community or youth groups rather than the classroom setting.

Building on the studies mentioned, this research frames the concept of student friend networks as an empirical phenomenon by applying several graph theory-based criteria into one analytical framework. Unlike prior works where researchers analyzed peer dynamics based on singular criteria, this investigation incorporates measures for centrality, clustering, density, and modularity to assess local behavior as well as overall network structures. The incorporation of several dimensions in the examination of cohesion, subgroups, and influencers in the social structure facilitates a richer appreciation of the dynamics in a community composed of numerous students. Moreover, by identifying the parallels between network structures and visible schools' groups such as strands, sections, and grades, the use of mathematics in the representation of peer networks is shown to have practical significance for understanding the workings of an educational institution. The findings may assist teachers and administrators in designing strategies that promote inclusivity, strengthen collaboration, and support student leadership development.

2. METHODOLOGY

2.1 Mathematical Concepts and Other Tools

The researchers used graph theory that had been widely used in social analysis since it can provide mathematical frameworks for the representation and investigation into the relationships among individuals, groups, or institutions. These relationships, represented by nodes-vertices and edges-links, allowed researchers to identify the hidden patterns, to determine influential actors, and to quantify structural properties of social systems. Hence, graph theory has become a more useful mathematical tool in analyzing the dynamics of social networks.

Gephi was the main platform used in applying graph theory through network visualization and analysis. According to Zonin (2024), Gephi was an open-source software meant for visualizing and analyzing large-scale graphs, providing functionalities for manipulating layouts, performing dynamic network analysis, and modular expansion using plugins, while scalable up to thousands of nodes and edges. Dyer (2022) has pointed out that Gephi can be used with minimal programming knowledge but still allow advanced mathematical functions required in graph theory, such as centrality, density, and modularity, relevant for real-world data. Gephi is an ideal environment for doing SNA and implementing Graph Theory since it combines powerful visualization capabilities with analytical techniques, which convert complex mathematical theories into understandable and useful insights. Its interactive graphs, like ForceAtlas2 or Fruchterman-Reingold, enable users to visualize networks and detect the cohesiveness, power, and connections within the graph. Additionally, the algorithms available in Gephi related to centrality, clustering, and modularity are directly linked with Graph Theory.

Using the software Gephi, the researchers were able to create a model to visualize the complexity of social networks. This software enabled the calculation of centrality scores to identify key individuals, density to measure the connectivity, and modularity to determine the community structures within the network. These results had been aligned with graph theory concepts and allowed for the mathematical quantification of social networks to be conducted. So far, integration with Gephi has been an effective means of transforming abstract mathematical measures into something visual and interpretable. In this way, Gephi was able to help social researchers identify patterns of influence, group formation, and network cohesion more effectively.

The authors also used ChatGPT-5 (OpenAI) to improve the clarity, fluency, and grammar of the manuscript sections. All suggestions made by the tool were carefully reviewed, revised and refined by the authors. The artificial intelligence tool was used for organization and no more than language enhancement, not for creating scientific ideas or conclusions. The authors are fully responsible for the accuracy and integrity of all content in the manuscript.

2.2 Data Collection

The research started with the creation of a peer nomination survey to identify the friendship structure among 597 senior high school students. Each participant was given a unique anonymous identification code corresponding to their academic track in a master list that was secured and accessible only to the researchers. The students were asked to nominate their classmates that they considered as friends or study buddies by writing down the codes instead of the names. Before the data collection, the researchers sought permission from the school administration and obtained informed consent from the participants.

In building the network, an edge was considered as a direct tie formed because of one student nominating another. Therefore, if student A nominated student B, a directed edge from A to B was formed. This method maintained the original structure of peer nominations. To interpret the results in an undirected manner, nominations between two students were considered as mutual ties. The weight of the edges was established based on the strength of the interaction as indicated in the survey responses. If two students were involved in various relational contexts, for instance, friendship and study partnership, or if the nominations were mutual, the tie was given a higher weight. As such, degree centrality is the number of unique connections a student has, while weighted degree is the intensity of the connections.

Figure 1. Friendship nomination survey conducted by the researchers.

Once gathered, the data was checked for repeated or incorrect answers and then transformed into an edge-list form, where every row consisted of a set of linked student IDs and a corresponding weight. The data was then loaded into Gephi software. The ForceAtlas2 algorithm was used to lay out the students in space based on the intensity of their links, enabling the formation of visible clusters. Various network metrics such as degree centrality, weighted degree, density, clustering coefficient, and modularity were calculated to determine the level of cohesion. By doing so, the research made sure that both visualization and statistical analysis were based on well-specified procedures for the construction of the network.

2.3 Statistical Treatment of Data

The graph theory measures were employed using the Gephi tool to analyze the structure and distribution of the student friendship network. The choice of metrics to be used in the analysis such as degree, weighted degree, density, clustering coefficient, eigenvector centrality, and modularity, was because each measure gives information on a different aspect of social connectivity that is relevant to the objectives of the study. Degree is a measure of the number of friendship ties that each student has, which indicates the level of social interaction or limitation of the classroom (Prochnow et al., 2024). Weighted degree considers the nominations that are repeated, which gives information on the strength of ties; a student with a high weighted degree is one who has been recognized multiple times as a friend or study partner, indicating their importance in the network (Cozzo et al., 2016).

Graph density is a measure of the overall cohesiveness of the network by comparing the number of actual ties to the maximum possible (Amure & Agarwal, 2025). Nodes are used to represent individual students, and they are the basis for all other measures of the network, with larger networks tending to have more complex patterns and smaller networks being denser (Saqr et al., 2024). Eigenvector centrality is used to identify the most influential students not only by the number of ties they have but also by the value of those ties (Newman, 2018). The clustering coefficient is a measure of how well a student's friends know each other, indicating the presence of tight peer groups (Cherifi et al., 2023). Modularity is a measure of the degree to which subgroups, such as clusters of students in different academic tracks, are formed and show the level of separation or integration among groups (Ouassif et al., 2025).

Finally, descriptive statistical analysis was employed to compare the friendship patterns across the tracks, enabling the researchers to detect differences in terms of connectivity, centrality, and subgroup structure. Taken together, the graph-theoretic and statistical analyses enabled a systematic and interpretable analysis of social cohesion, group formation, and key players in the senior high school setting.

3. RESULTS AND DISCUSSION

The network visualizations derived through Gephi provided a descriptive overview of how students connect and cluster within the social network. Each node represented one student, while each edge represented one friendship tie. This network had 597 nodes and about 2,985 edges, showing that this is a moderately connected structure representative of the general pattern of interaction among students.

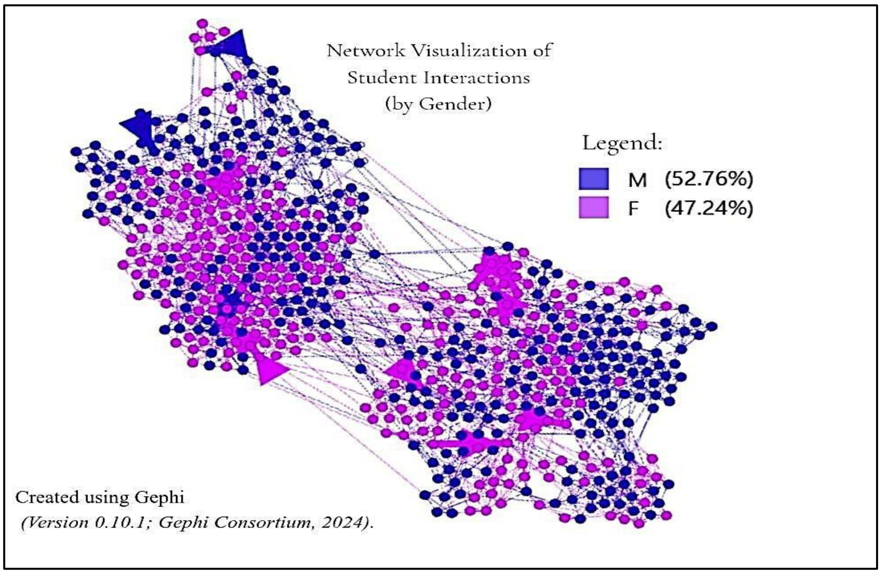

Figure 2. Network visualization of student interactions (by gender).

The gender-based visualization showed that male students were well represented in the network with 52.76% and female students with 47.24%. However, most female students were found near the center of the visualization, surrounded by clusters of male students. Gender homophily is noticeable in the figure but not to the degree of division. The said pattern serves as a good indicator that female students often serve as bridges or connectors among male-dominated groups, improving communication and social balance. In such a context, it is expected to note the presence of several central female nodes within a highly integrated and cohesive network, indicating that gender is not serving as a dividing factor in student interactions but, rather, is contributing to overall network stability and inclusivity (Garrote et al., 2023).

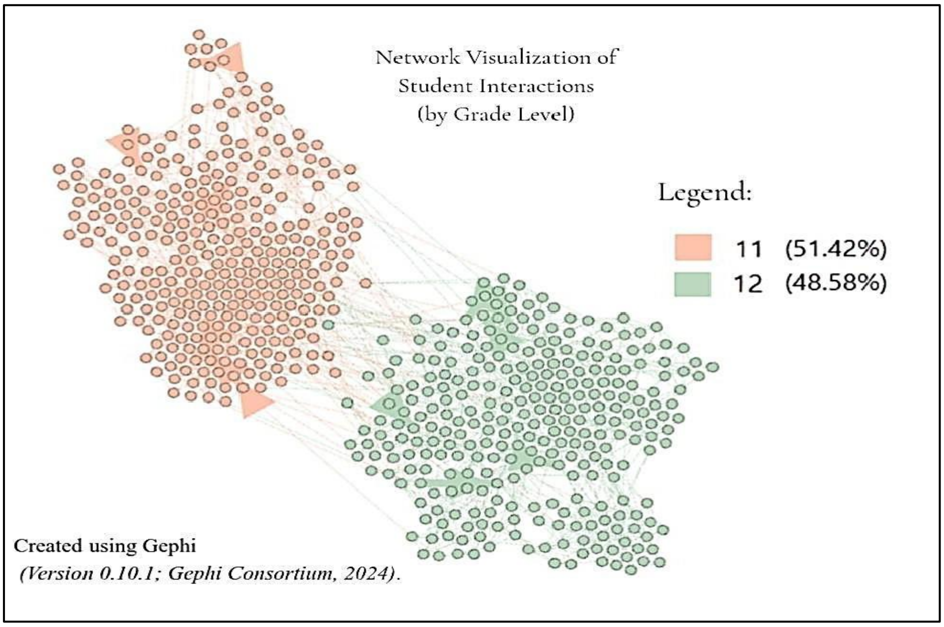

Figure 3. Network visualization of student interactions (by grade level).

Figure 3 presented two clear-cut yet interconnected clusters, with Grade 11 in orange at 51.42% and Grade 12 in green at 48.58%. Individually, students expressed a tendency toward stronger associations within their own grade level, reflecting academic and social familiarity. At the same time, however, the presence of several links between the clusters serves to illustrate that friendships across grades also do exist. Such an arrangement reveals a network with considerable separation but, at the same time, a unified one. This means that both grade levels remain socially connected, and friendships transcend academic year boundaries. Such webs of connection facilitate peer cooperation and help knit a school together.

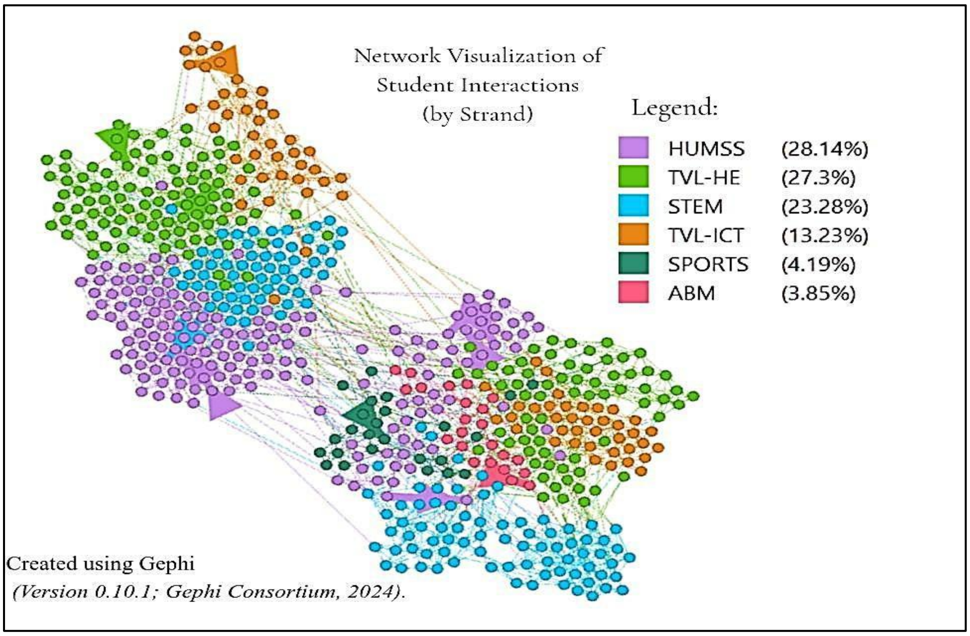

Figure 4. Network visualization of student interactions (by strand).

The strand network visualization highlighted distinct clustering across the six academic tracks, with Humanities and Social Sciences (HUMSS) comprising 28.14%, Technical-Vocational and Livelihood- Home Economics (TVL-HE) 27.3%, Science, Technology, Engineering, and Mathematics (STEM) 23.28%, Technical-Vocational and Livelihood- Information and Communications Technology (TVL-ICT) 13.23%, Sports 4.19%, and Accountancy, Business, and Management (ABM) 3.85%. Every strand in the graph formed clear clusters, suggesting that students are more frequently interacting with peers in the same track, a form of strand-based grouping. Even so, inter-strand connections are still apparent in the graph, meaning that academic specialization does not restrain social interaction. Notably, in the overall network, the HUMSS strand is positioned in the center as it seems to occupy a connector position among the other strands. Second, considering previous visualization in Figure 3, it is worth noting that, in the grade 11 region, STEM students appear to be in the central position. In the Grade 12 region, it shows more mixed strands in the center of the network, having the HUMSS learners at its core. These centricities reflect higher levels of social engagement and diversity in peer relationships. Thus, the pattern supports such a concept of academic homophily, where students sharing learning contexts interact more, yet still maintain a connected school community (Horta et al., 2022).

The network visualization (Figure 5) of sections showed several distinctly separated clusters corresponding to classroom sections, named by virtues, in proportions ranging from INGENUITY at 6.7% to INTEGRITY at 2.85%. The internal networks for each section were dense, but several interconnecting edges between clusters indicated active cross-sectional communication. The Fortitude section was centrally positioned in the network, which places its students as bridges connecting other sections and grade levels. Several sections were situated near the middle but in different directions, while others appeared more to the outer sides of the visualization. This suggests that some sections are highly interactive and socially central, while others are within their own group.

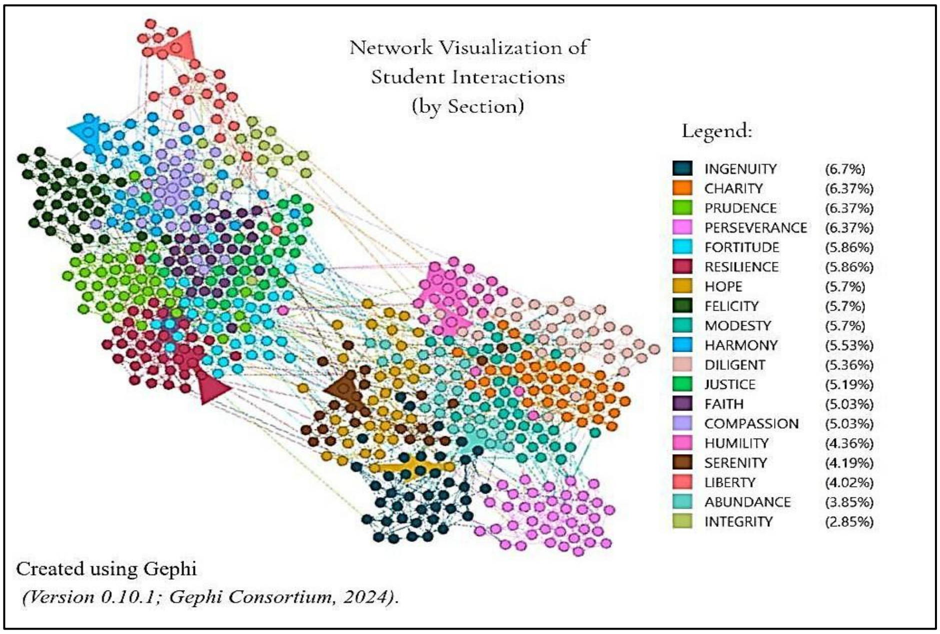

Figure 5. Network visualization of student interactions (by section).

Altogether, the visual analyses of the data indicate a moderately clustered yet highly cohesive student friendship network, with group-based clusters by gender, strand, and section that remain interconnected through bridging individuals, especially female students, members of the HUMSS strand, and students from Fortitude section, who hold more central positions within the network. These network patterns indicate that, while social interactions do indeed follow academic and organizational divisions, there is a strong sense of cohesion and cooperation amongst the whole population of students. The cohesion visibly evident here reflects the principles of Social Network Theory, where the ideal state in a school network strikes a balance between membership in a group and connectivity among groups.

Table 1. Statistical Analysis of Student Networks (generated through Gephi)

Average Degree	4.972
Graph Density	0.008
Average Weight	4.998
Modularity	0.678
Number of Communities	13
Average Clustering Coefficients	0.236
Total Triangles	1265
Eigenvector Centrality Yield	0.095

The network produced an average degree of 4.972, shown in Table 1, indicating that each student maintained approximately five close peer connections. In social network analysis, degree centrality reflects the number of direct ties maintained by a node and serves as an indicator of immediate relational activity. This suggests moderate interpersonal engagement within the department. Despite this, the overall graph density was 0.008, meaning that only a small proportion of all possible connections were present. In large social systems, low density is expected because individuals typically form selective rather than universal connections. Thus, while structurally sparse, the network does not imply fragmentation but rather patterned social organization (Garrote et al., 2023).

The average weight of 4.998 suggests that reported friendships were relatively strong, indicating stable peer affiliations. At the local level, the average clustering coefficient of 0.236 reveals moderate cohesion among students' immediate circles. Clustering coefficients measure the extent to which an individual's friends are also connected to one another, reflecting triadic closure and localized group bonding. The presence of 1,265 total triangles further supports the existence of tightly knit peer clusters, as triadic structures are widely associated with trust formation and shared group identity in social systems.

Community detection analysis yielded a modularity score of 0.678 and identified 13 distinct communities within the network. Modularity values above 0.4 are generally interpreted as evidence of meaningful subgroup structure. A score of 0.678 indicates strong internal cohesion within groups while still allowing intergroup connectivity. This suggests that while students naturally cluster, possibly by academic strand or shared context, the overall network remains integrated rather than socially segmented.

Eigenvector centrality yielded a value of 0.095, indicating the presence of students who are not only well connected but also connected to other highly connected peers. Unlike simple degree measures, eigenvector centrality captures the relative influence of nodes based on the prominence of their neighbors. This finding suggests that certain students occupy structurally influential positions that may facilitate communication and cohesion across the broader network.

Overall, the structural properties of the network indicate a moderately connected, yet selectively organized student body characterized by identifiable peer clusters, localized cohesion, and influential actors embedded within an integrated system. Consistent with previous applications of graph theory in educational contexts, the findings suggest that the department maintains a balanced social structure in which subgroup identity coexists with overall connectivity. Such structural patterns provide insight into how peer relationships may support collaboration, inclusion, and peer- based academic support within secondary school settings.

Table 2. Nodes Ranking with most numbers of ties.

Ranking	Student Code	Number of Ties	Gender	Grade Level	Strand	Section
1	S119	27	Female	11	HUMSS	Resilience
2	S209	22	Male	11	HUMSS	Felicity
3	S321	21	Male	12	STEM	Perseverance
4	S320	20	Male	12	STEM	Perseverance
4	S322	20	Male	12	STEM	Perseverance
5	S035	19	Male	11	STEM	Justice
5	S535	19	Female	11	TVL-ICT	Charity
5	S111	19	Female	12	STEM	Resilience
6	S325	18	Male	12	STEM	Perseverance
6	S110	18	Female	11	HUMSS	Resilience

Table 2 presents the list of students with the highest number of social ties, arranged by section and strand. From the data, it can be observed that most of the top students are from the HUMSS and STEM strands, especially from the sections Resilience, Felicity, and Perseverance. In detail, the top three students, in order, were S119 from HUMSS-Resilience with 27 ties, S209 from HUMSS-Felicity with 22, and S321 from STEM-Perseverance with 21. Other top-ranking students belong to the STEM and HUMSS strands, which evidence that learners from these strands play a vital role in building and maintaining strong social connections within the school network.

These results indicate that some students serve as key connectors who act to maintain communication and interaction among their classmates. According to (Whelan, 2023), a student who has many connections often acts as a contact point within the group to whom others are informed and connected. It also revealed that having students with many social links aids in teamwork and inclusiveness inside a school setting. Having said connector individuals in a community strengthen trust, friendship, and cooperation among students to create a healthy learning environment.

4. CONCLUSIONS AND RECOMMENDATIONS

This study investigated how graph theory and social network analysis describe the connectivity and interaction among senior high school students from a school in the City of Malolos. It was determined that most of the students belonged to a single, large, connected network, each maintaining five close friendships. Although many students stick to friends within their strand, rich relationships can be built across different academic groups. In fact, a modularity score of 0.678 confirmed that friendships naturally cluster by strand and section, yet the presence of cross-strand links proved that students interact beyond academic boundaries. Centrality measures showed a few individuals act as connectors to help maintain communication between groups, and the clustering patterns evidenced small, stable circles within one united community.

Based on these findings, the study recommended several data-driven projects and school policies which further promote unity, inclusiveness, and student well-being. This includes designing a project that creates a system for automatically generating and updating friendship network maps using Gephi data, enabling teachers to track social interaction patterns in real-time. Similarly, another application of the idea is a peer support application to identify potential peer mentors and match them with other students who are less active in social circles by making use of eigenvector and betweenness centrality. An interactive strand-based cluster, cross-strand interactions, and overall social structure visualization in the school may also be built to help administrators visualize more strategically for better planning and organizing of collaborative activities. Such data-informed projects would assist the guidance of homeroom teachers in forming balanced friendships among students, improving communication, and nurturing a socially cohesive classroom atmosphere that encourages both personal and academic growth.

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