

# A Study on the Association between Peer Relationships and Academic Performance in Cooperative Learning in Chinese Middle Schools

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## Abstract

Cooperative learning has been widely implemented in the field of education; however, the influence of peer interaction on learning outcomes remains insufficiently explored. This study aims to uncover the dynamic relationship between peer relationships and academic performance within a cooperative learning context. Using a cluster sampling method, 118 first-year junior high school students from a school in Chengde, China, were selected and assigned to 12 cooperative learning groups. Individual and social network data were collected via WeChat. The Stochastic Actor-Oriented Models (SAOMs), supported by RSiena software, were employed to analyze data on social closeness, academic support relationships, and academic achievement, distinguishing between peer selection and influence processes. The findings reveal that the two types of peer relationships are closely linked and mutually reinforcing. Students with higher academic performance are more likely to be selected as academic supporters and are more proactive in establishing close social and academic support relationships. However, peer relationships do not have a significant effect on academic performance. The study concludes that peer dynamics in cooperative learning are complex and primarily contribute to shaping the social structure. These results offer a new perspective for understanding the mechanisms of cooperative learning.

**Keywords:** cooperative learning, peer relationships, academic performance, social network analysis, stochastic actor-oriented models

## 1. Introduction

Cooperative learning, as a teaching model that emphasizes the interdependence and active interaction among group members, has been widely applied at all educational levels globally (Johnson & Johnson, 2019). Its theoretical foundation is rooted in social constructivism, which posits that knowledge is co - constructed during social interactions (Wentzel, 2018). Through group interactions, students can deepen their understanding and enhance their learning effectiveness through mutual assistance and communication. Although numerous studies have affirmed the educational effectiveness of cooperative learning, in practical applications, there is still a lack of systematic exploration into how peer interaction relationships shape learning outcomes. Therefore, this paper focuses on the dynamic relationship between peer relationships and academic performance in the context of cooperative learning, aiming to provide a new empirical basis for understanding the mechanism of cooperative learning.

In a cooperative learning environment, peer relationships not only influence students' social adaptation but may also have a profound impact on their academic performance (Smith et al., 2020). Positive peer relationships can enhance students' sense of belonging, learning motivation, and engagement, thereby improving learning outcomes (Brown et al, 2021). For example, Johnson (2020) found in their study that students in positive peer relationships are more willing to actively participate in classroom discussions and share their ideas and thoughts. Such interactions can stimulate students' thinking and deepen their understanding of knowledge. On the contrary, negative peer interactions may undermine learning outcomes, causing students to develop negative emotions and reducing their learning enthusiasm (Gillies, 2019). Smith et al. (2021) conducted surveys in multiple schools and found that students with peer conflicts are more likely to be distracted during learning and tend to have relatively lower academic performance. Therefore, studying peer relationships in a learning community, especially within the framework of

cooperative learning, is of great practical and theoretical significance. An in-depth exploration of how students establish academic and social support relationships in cooperative learning can help optimize group composition and instructional design, thereby further enhancing the effectiveness of educational interventions (Wang & Liu, 2021).

Existing research on cooperative learning generally shows that cooperative learning can help students achieve multiple academic goals. Some studies emphasize that cooperative learning can enhance students' cognitive achievements, such as improving their comprehension and critical thinking abilities (Hmelo-Silver, 2020). Lee and Kim found through experimental research that students participating in cooperative learning performed significantly better than those in traditional learning modes in reading comprehension and logical reasoning tests (Chen & Zhang, 2021). The study by Wang and Liu (2018) also confirmed that cooperative learning can stimulate students' critical thinking, enabling them to analyze and solve problems more comprehensively and deeply. Other studies indicate that cooperative learning is conducive to skill development, including the cultivation of problem-solving abilities and self-regulated learning strategies (Zhao & Sun, 2020). Chen and Zhe (2022) found through long-term follow-up research that in a cooperative learning environment, students' ability to solve complex problems gradually improves, and they can better use self-regulated learning strategies to manage the learning process. The research by Zhao and Sun (2020) further shows that cooperative learning provides students with more opportunities for practice and reflection, which helps cultivate their autonomous learning ability. Meanwhile, there are also studies highlighting the shaping and promotion of teamwork abilities through cooperative learning.

However, most of these studies focus on the overall impact of cooperative learning on learning outcomes, and there are few in-depth explorations of the dynamic mechanisms by which peer relationships contribute to the improvement of academic performance. Although existing studies recognize the importance of peer relationships, there is still a lack of systematic research on how peer relationships specifically affect academic performance in cooperative learning and the dynamic change process of such influence (Fang & Xu, 2021). Davis et al. (2021) pointed out that currently, the relationship between peer relationships and academic performance is mostly analyzed statically, failing to fully consider the dynamic changes in the influence of peer relationships on academic performance over time and with changes in the learning stages. Fang and Xu Liu (2021) also argued that when exploring the relationship between peer relationships and academic performance, existing studies often overlook the differences in the influence mechanisms of peer relationships in different subject learning contexts. Therefore, this paper intends to introduce the social network analysis method, focus on the evolution process of peer relationships in cooperative learning, especially how social closeness relationships and academic support relationships jointly affect the changes in academic performance, in order to provide a new empirical perspective for understanding the internal mechanisms of the effectiveness of cooperative learning.

Current research on the relationship between social networks and academic performance in the field of middle school education has significant limitations. Firstly, some studies mainly rely on students' self - perception data to evaluate social integration. For example, they collect individuals' subjective evaluations of their own social relationships through questionnaires. This method is vulnerable to social desirability bias and memory bias (Wentzel et al., 2018). Secondly, although some other studies pay attention to peer relationships, they lack dynamic measurements based on complete longitudinal network data, making it impossible to accurately capture the real - time evolution trajectory of peer relationships over time (Ripley, 2021). These two limitations have restricted our in - depth understanding of the impact mechanism of peer interactions on academic performance in cooperative learning. To address these shortcomings, this study uses longitudinal peer network data based on cooperative learning groups and applies the Stochastic Actor - Oriented Models (SAOMs) to capture the co - evolutionary process of students' peer networks and academic performance over time. This represents an important innovation in research design and methodology.

This study is innovative in three aspects

1. Focus on the dynamic interplay between peer relationships and academic performance:

Unlike previous research that has predominantly examined the overall impact of cooperative learning, this study investigates how socially close relationships and academic support relationships co-evolve and jointly influence academic performance. By exploring these dynamics longitudinally, the study provides new empirical insights into the mechanisms of peer interaction within cooperative learning environments.

2. Simultaneous examination of two interrelated social networks

Prior studies have tended to focus on either social or academic peer networks in isolation. This study contributes by integrating both socially close and academic support networks in its analysis, offering a more comprehensive view of peer interactions and their respective roles in cooperative learning contexts.

### 3. Application of advanced social network modeling to educational research

Methodologically, the study utilizes longitudinal complete-network data from junior high school cooperative learning groups and applies Stochastic Actor-Oriented Models (SAOMs) via RSiena software. This approach enables the analysis of co-evolutionary processes between peer networks and academic performance over time. It also overcomes common limitations in existing literature, such as reliance on static data or students' self-reported perceptions, thereby enhancing the validity and robustness of findings.

## 2. Method

### 2.1 Sample and Educational Context

In this study, the cluster sampling method was employed to select first - year junior high school students from a school in Chengde, China. Follow - up surveys were conducted twice, with a six - month interval between each survey. After excluding invalid questionnaires, a total of 118 valid questionnaires were obtained. Among the participants, there were 62 female students and 56 male students, with an average age of 12.37 years. These students were divided into 12 cooperative learning groups, with approximately 10 students in each group. All the cooperative learning groups had the same learning progress. Besides collaborating in class, the members of the cooperative learning groups would also meet after class to work on group assignments.

### 2.2 Procedure

This survey research was approved by the school's ethics committee. Surveys were conducted among students at the end of the 2023 - 2024 academic year, with a total of two surveys. WeChat was used to collect relevant information, including personal and social network - related information. Before distributing the questionnaires, the researchers explained the purpose and procedures of this study to both teachers and students. The researcher received assistance from school staff during data collection. Homeroom teachers helped organize the survey sessions, and IT staff supported the distribution of questionnaires through the WeChat platform. The academic office also provided anonymized academic records. All support was approved by the school and complied with ethical guidelines.

### 2.3 Measures

#### 2.3.1 Socially Close Relationships

Students were required to nominate which classmates within the same department were their socially close acquaintances or were likely to become socially close to them (Martínez & López, 2019). For each nominated classmate, students were asked to rate on a 6-point scale. A rating of 1 represented "the closest relationship", 2 represented "a close relationship", 3 represented "a friendly relationship", 4 represented "an ordinary relationship with not much in common", 5 represented "only know each other by appearance or name", and 6 represented "completely unfamiliar" (this scale was adapted from Van de Bunt, 1999). During data analysis, to simplify and highlight the key points, we combined the categories from "the closest relationship" to "a friendly relationship" into 1, defined as "a socially close relationship exists"; and combined the other categories into 0, defined as "a socially close relationship does not exist". Through this approach, we were able to clearly measure the socially close relationships or potential socially close relationships among students.

#### 2.3.2 Academic Support Relationships

Students were required to indicate which classmates within the same department they would turn to for academic advice or support when they had questions about the learning materials (Liu and Zhao, 2020). The responses were measured using a five-point Likert scale, ranging from "strongly disagree" to "strongly agree", with an additional option of "do not know this classmate". In the analysis, the options of "strongly agree" and "agree" were combined into 1, representing "an academic support relationship exists"; and the remaining options were combined into 0, representing "an academic support relationship does not exist". This measurement method effectively reflected the students' relationship network in terms of academic support.

#### 2.3.3 Academic Performance

This study was officially authorized by a middle school in Chengde, China, and the student performance data were obtained from the school system to ensure that the data truly reflected the students' academic performance. Secondly, to meet the requirements of the RSiena software in this study for the data format of the dependent variable, it was necessary to reasonably transform the original scores. The original final exam scores were continuous data, while the RSiena software required the dependent variable to be ordinal data. Therefore, the rounding method was adopted to uniformly convert the final exam scores of the first and second semesters of the first year of junior high school into

ordinal data on a scale of 1 to 9. This conversion process was checked multiple times to ensure the accuracy and consistency of the data, laying a solid foundation for subsequent precise analysis (E. Fernandez, 2020).

#### 2.3.4 Statistical Analysis

When exploring the complex relationships among students' socially close relationships, academic support relationships, and academic performance in the context of cooperative learning, this study selected the Stochastic Actor - Oriented Models (SAOMs) and conducted in - depth analysis with the help of the RSiena software package in R language.

At the beginning of the research design, to accurately identify the selection effect, it was necessary to have a comprehensive understanding of all students in the network, including those who were not selected. Therefore, the research scope was defined within a group with specific social significance. In this study, 12 cooperative learning groups of first - year junior high school students from a school in Chengde, China were selected, and complete longitudinal network data of these groups were obtained. Based on this, two key models were constructed to analyze the co - evolution of social networks (students' socially close relationships or academic support relationships) and academic performance. For each model, a rate parameter was set for the dependent variable, which can intuitively show the frequency of students changing their relationships or academic performance, and further quantify the trend of these changes (Wilson, 2022).

When constructing the relationship change model, to ensure the accuracy and reliability of the research results and avoid biases in the estimation of selection and influence effects, a series of structural network effects were included as control variables in this study. The out - degree (density) reflects the internal tendency of students to establish relationships, representing the intensity of students' willingness to actively expand their socially close relationships or academic support relationships. Reciprocity reflects students' tendency to respond to others' relationship nominations, which is an embodiment of the reciprocity of relationships (Ali & Khan, 2020). Transitivity is used to capture the trend of students forming interconnected groups, such as the phenomenon of "friends of friends becoming friends". The transitive reciprocal triple, as an interaction term of reciprocity and transitivity, can analyze the probability change of reciprocal relationships occurring within transitive groups. In - degree popularity measures the likelihood of students receiving additional nominations when they have already received a large number of relationship nominations. In the class, students with excellent academic performance and a helpful attitude often have a high in - degree popularity. Classmates are not only willing to establish relationships with them, but also more classmates will want to be close to them later. Out - degree activity represents the tendency of students to nominate others further when they have numerous relationships, while in - degree activity describes the behavioral tendency of students to actively nominate others after being nominated. By incorporating these structural network effects as control variables, the model can more accurately disentangle the intricate mechanisms underlying relationship formation and evolution. This not only enhances the robustness of the study's findings but also provides a more nuanced understanding of how students' social behaviors within the classroom context contribute to the shaping of their relationship networks. Ultimately, these control variables serve as crucial tools for teasing apart the confounding factors that might otherwise obscure the true nature of the selection and influence effects, thereby enabling a more precise and reliable exploration of the dynamics at play in students' social interactions.

In the selection model part, an exogenous network effect was introduced, that is, the relationships in one network will have an impact on the formation of relationships in another focal network. For example, in real learning life, students usually seek academic support from their close classmates, or establish closer relationships with classmates who have provided them with academic support. At the same time, the model also incorporated the self - effect (sender effect), other - effect (receiver effect), and similarity effect (homophily). The self - effect measures the degree to which students with specific characteristics actively nominate others. For example, extroverted students may be more proactive in establishing relationships with others; the other - effect captures the frequency of students with certain characteristics being nominated by others. Students with good academic performance are often more likely to be selected as academic support objects by other classmates; the similarity effect considers the possibility of students establishing relationships due to characteristics such as the same gender or being in the same cooperative learning group. For academic performance, the interaction effect between self - academic performance and others' academic performance can reflect the influence of the similarity of students' academic performance on relationship establishment. If the estimated value of the exogenous network effect is positive, it indicates that students are more inclined to establish relationships with classmates with similar academic performance (Boedien, 2016).

To comprehensively capture the complex interplay between peer relationships and academic performance, an influence model was constructed. This model was designed with a specific focus on elucidating the dynamics of

academic performance changes. It incorporates the standard effects of the linear and quadratic forms of the academic performance distribution, where the linear component serves to illustrate the overarching trend of performance changes at the extreme ends of the performance spectrum (Yamamoto, 2021). For example, whether the overall performance rises or falls as the semester progresses. The quadratic form reflects the degree of dispersion of performance. A negative quadratic form effect indicates that the performance regresses to the mean, just like students with large initial performance differences gradually tend to have more similar performance after a period of study; a positive effect means performance polarization, that is, students with good performance perform even better, and students with poor performance perform even worse. The influence of relationship degrees on academic performance varies depending on the type of relationship. In academic support relationships, two situations are distinguished: seeking support (out - degree - academic performance) and providing support (in - degree - academic performance); in students' socially close relationships, the influence of deep relationships on academic performance (reciprocal degree - academic performance) is evaluated through "true close relationships" (mutual nominations). In addition, the model also incorporated the effect of the average academic performance of friends or helpers in mutual nomination relationships on students' own performance, as well as the gender variable, to explore the performance differences between male and female students.

During the model testing stage, some Stochastic Actor - Oriented Models for similar effects of students' socially close relationship networks and academic support relationship networks failed to reach an ideal convergence level. Finally, A post-hoc analysis was conducted in accordance with the approach proposed by Ripley et al (2022). This analysis integrated the log odds derived from the self - effect, other - effect, and their interaction effects. By doing so, it simulated the influence of the temporal changes in academic performance on students' selections of academic support providers and close peers. The ultimate aim was to identify the relationship - selection propensities of students at varying performance levels.

### 3. Results

#### 3.1 Network Descriptive Statistics

The density characteristics of social networks were given special attention in this study. The data showed that the degree of closeness of relationships within the cooperative learning groups in both the socially close relationship network and the academic support relationship network was significantly higher than that outside the groups (see Table 1). Over time, from semester one to semester two, the network density within the cooperative learning groups showed a downward trend (Snijders & Koskinen, 2022). In the first semester, regardless of whether it was the socially close relationship network or the academic support relationship network, the interaction among students within the groups was stronger than that outside the groups, and the interaction in the socially close relationship network was the most frequent. Specifically, in a cooperative learning group with an average size of 10 students, each student had an average of 3 close classmates in the first semester, which decreased to 2 in the second semester. In terms of academic support, students on average chose 3 classmates as the objects to seek academic support in the first semester, and this number decreased to 2 in the second semester. In contrast, outside the cooperative learning groups, students maintained an average of 3 close classmate relationships in both semesters, and the situation of seeking academic help from 2 - 3 classmates was relatively stable. This indicates that after the first semester, the interaction between students and classmates outside the groups increased.

**Table 1.** Descriptive Network Statistics

Semester	Socially close relationships		Academic support relationships	
	1	2	1	2
Spatial Autocorrelation of Peer Relationship Networks				
Moran's I Index of Academic Performance	0.13	0.11	0.18	0.12
Geary's C Index for Academic Performance	0.63	0.87	0.54	0.69
Network statistics				
Within cooperative learning group				
Network Density (%)	36	27	29	19
Reciprocity (%)	52	49	41	49

**Table 1.** Descriptive Network Statistics(Continued)

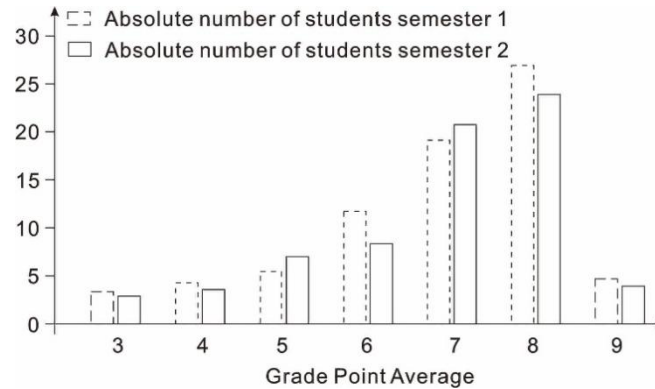
Semester	Socially close relationships		Academic support relationships	
	1	2	1	2
M degree	3.25	2.29	3.12	1.62
Standard Deviation of Indegree Values	1.81	1.77	1.71	1.51
Standard Deviation of Outdegree Values	2.71	2.21	2.52	1.67
Data Coverage Beyond Cooperative Learning (Whole Study Programme)				
Network Density (%)	3	3	3	2
Reciprocity (%)	48	62	42	52
M degree	3.22	3.17	2.54	2.37
Standard Deviation of Indegree Values	2.85	2.68	2.46	2.31
Standard Deviation of Outdegree Values	2.63	2.72	2.14	2.27
Change in relationships				
Jaccard Index for Relationship Stability	0.41		0.39	
Number of Dissolved Relationships (Status Change from 'Existent' (1) to 'Nonexistent' (0))		315		294
Number of Newly Emerged Relationships (Status Change from 'Nonexistent' (0) to 'Existent' (1))”		194		142
Number of Maintained Relationships (Remaining in the 'Existent' State (Coded as 1))		302		246
Note: In each network, N = 102 (number of students). The number of dyads is $102 \times 101 (N - 1) = 10302$ . As each dyad provides 2 observations, the total observations per network are $10302 \times 2 = 20604$ .				

In addition, the result that the Jaccard similarity index exceeded 0.35 indicates that the data from consecutive surveys have good stability, which provides strong support for the reliability of the statistical parameter estimation in subsequent studies and ensures that the models constructed and the analysis conclusions based on these data have a solid foundation.

### 3.2 Performance Level

In this study, students' academic performance was measured by calculating the weighted average grade point average (GPA), covering the data of the first and second semesters. In the first semester, the mean value of students' GPA was 6.18, the median was 6.89, and the standard deviation was 1.68. In the second semester, the mean value decreased to 5.23, the median was 6.26, and the standard deviation increased to  $SD = 2.45$  (see Figure 1). In terms of the performance distribution, the largest number of students fell within the score range of 7 - 8. The Geary's C network autocorrelation coefficient and Moran's I index were used in this study to analyze the distribution characteristics of students' performance in the network and its correlation with the network. The Geary's C coefficient showed that in both the socially close relationship network and the academic support relationship network, this coefficient fluctuated between 0.54 and 0.87 (see table 1), and it approached 1 over time, indicating that the gap in academic performance among students gradually increased, and the correlation of performance decreased. The Moran's I index showed a downward trend and approached 0 from semester one to semester two, further indicating that the correlation of performance in the two networks gradually weakened (Chen & Chang, 2022).

From semester one to semester two, the differences in academic performance among students gradually increased, and the correlation of performance in the socially close relationship network and the academic support relationship network continued to decrease. This indicates that in the cooperative learning environment, over time, the guiding role of performance in students' construction of social relationships and seeking of academic help has been continuously weakening. It may be that after students adapt to middle school life, other factors such as personality traits play an increasingly important role in the establishment of interpersonal relationships. This result provides a new perspective for studying the factors that promote students' interaction and cooperation in cooperative learning. When educators promote the development of students' relationships, they need to consider more diversified influencing factors.



**Figure 1.** Comparison of Academic Performance (GPA) Distributions between the First and Second Semesters. Note: The sample includes students who failed the exams.

### 3.3 Results of the Co-Evolution Models

In this study, the co-evolution model was used to conduct an in-depth analysis of the relationships among the socially close relationship network, the academic support relationship network, and academic performance. The results are presented in the form of estimated values and standard errors. When the absolute value of the estimated value divided by the standard error is greater than or equal to 2, the results are statistically significant.

#### 3.3.1 Endogenous Structural Effects

**Table 2.** Endogenous Network Effects Table

Effects	Explanation	Socially close relationships	Academic support relationships
<b>Selection network mechanism</b>			
Rate period ties	The rate of change in network connections over time, representing how often students can change their relationships.	12.45** (1.51)	9.11c** (1.57)
<b>Endogenous network effects</b>			
Outdegree (density)	The tendency of a student to initiate new relationships, indicating the number of connections a student actively makes with others.	-2.46 (0.51)	2.35 (0.71)
Reciprocity	The degree to which relationships are reciprocal, reflecting the likelihood that if student A nominates student B, student B will also nominate student A.	3.12** (0.42)	3.42** (0.52)
Transitive Triplets in Peer Relationship Networks	The tendency of students to form transitive relationships: if A has a relationship with B and B with C, A is likely to relate to C.	0.62** (0.11)	0.82** (0.22)
Reciprocated Transitive Triplets in Peer Relationship Networks	The likelihood of reciprocal relationships in transitive groups. For example, if A has a reciprocal relationship with B, and B with C, it's the probability that A and C will also be reciprocal.	-0.47 (0.12)	-0.62 (0.22)
Outdegree-activity	The likelihood of students with many outgoing relationships starting new ones.	0.09c (0.09)	-0.11 (0.10)
Indegree-activity	The likelihood that students with many incoming nominations will nominate others. A negative value may suggest they're cautious about new relationships or content with their current networks.	-0.41 (0.11)	-0.51 (0.21)

Note: In social network analysis, 'Ego' is the relationship - initiator, 'Alter' the receiver. \*\* means  $P < 0.05$ ; results are significant when unrounded estimate/SE  $\geq 2$ . Both models had 5000 iterations, with a max convergence ratio of 0.18 for reliable estimation.

The data show (see Table 2) that the out-degree effect is negative, which means that the number of socially close acquaintances and academic support providers selected by students in the learning projects is less than half of the total number of classmates. In both the socially close relationship network and the academic support relationship network, students tend to establish reciprocal relationships (the reciprocity effect is positive), and they are more willing to form relationship clusters (the transitive triad effect is positive). The parameter of the transitive reciprocal triad is negative, indicating that the strength of reciprocal relationships within cooperative learning is lower than that among groups outside of cooperative learning. In the socially close relationship network, the out-degree - activity parameter is significantly positive, indicating that socially active students are more likely to expand their relationships. The in-degree - activity effect is significantly negative in both networks, which may be because students who have received a large number of nominations are more cautious when choosing new relationships, or they are already satisfied with their existing social circles.

This investigation in the study can well explain a common phenomenon in cooperative learning: the top students in the class often have many classmates asking them questions every day. Over time, these excellent students may choose to help those classmates whom they think are more worthy of help or have a closer relationship with them, rather than helping all the classmates who ask for assistance.

### 3.3.2 Selection of Socially Close Acquaintances and Academic Support Providers

**Table 3.** Exogenous Network Effects Table

Effects	Explanation	Socially close relationships	Academic support relationships
<b>Selection network mechanism</b>			
Socially close relationships			1.44** (0.31)
Academic support relationships		0.81** (0.19)	
<b>Covariates</b>			
Gender (F) alter	A student (ego) is more likely to nominate a fellow student (alter) if the alter is female (coded as 1, with male coded as 0).	-0.31 (0.22)	-0.79 (0.31)
Performance ego	Female students are more likely to take the initiative to establish connections outside the cooperative learning group.	-0.41** (0.21)	0.21 (0.35)
Same gender (F)	Connections between two students of the same gender are more likely to occur (homophily effect).	0.81** (0.24)	0.87** (0.36)
Performance alter	The higher the performance of a fellow student (alter), the more likely a student (ego) is to establish a connection with this alter.	0.24** (0.11)	0.87** (0.29)
Performance ego	The higher the performance of the focal student (ego), the more likely this student is to be connected to (popularity effect).	0.52** (0.21)	0.88** (0.39)
Interaction Effect between Ego's Academic Performance and Alter's Academic Performance	There is a greater possibility of a connection (homogeneity effect) between two students with similar performance levels.	0.08 (0.06)	0.05 (0.07)
Same LC	Two students from the same cooperative learning group are more likely to have a connection (homogeneity effect).	-0.07 (0.21)	-0.34 (0.24)



Note: In social network analysis, 'Ego' is the relationship - initiator, 'Alter' the receiver. \*\* means  $P < 0.05$ ; results are significant when  $|\text{unrounded estimate}/SE| \geq 2$ . Both models had 5000 iterations, with a max convergence ratio of 0.18 for reliable estimation.

In terms of selecting socially close acquaintances, when students seek academic support from each other, they are more likely to develop closer socially close relationships (the effect of socially close relationships is positive) (Wang, & Ma, 2022). Students with higher academic performance are more likely to be regarded as socially close acquaintances (the other-effect of academic performance is positive), and they are also more proactive in establishing socially close relationships (the self-effect of academic performance is positive), and these effects are more pronounced in seeking academic support (see Table 3).

However, the similarity in academic performance has no significant impact on establishing socially close relationships, and being in the same cooperative learning group does not increase the likelihood of establishing relationships. In terms of gender, females are nominated as socially close acquaintances and initiate relationships less frequently than males. Students of the same gender are more likely to establish socially close relationships. This indicates that there is a close connection between academic support and socially close relationships, and academic performance plays an important role in establishing social relationships, but it is not the only factor. The process of students seeking academic support promotes the development of social relationships, and students with excellent academic performance are more attractive and proactive in social interactions.

When selecting academic support providers, students tend to establish academic support relationships with their socially close classmates (the effect of academic support is positive), and they often seek help from students with excellent academic performance (the other-effect of academic performance is positive). Students with excellent academic performance are also more proactive in initiating academic support relationships (the self-effect of academic performance is positive). The similarity in academic performance cannot effectively explain the behavior of seeking academic support, and students will not establish academic support relationships more frequently just because they are in the same cooperative learning group. In terms of gender, the probability of females being sought for academic support is lower than that of males, and students of the same gender are more inclined to seek support from each other. This shows that socially close relationships and academic performance play a crucial role in the selection of academic support providers. Students seek help from their close classmates based on social trust, and at the same time, they recognize the abilities of students with excellent academic performance. The irrelevance of the similarity in academic performance may be because solving academic problems depends more on professional knowledge and abilities rather than the degree of similarity in academic performance.

### 3.3.3 Influence of Academic Support Relationships and Socially Close Relationships on Academic Performance

After analyzing the data from the co - evolution models, this research found no clear patterns in how academic performance changed. Specifically, the effects related to the rate of change in academic performance, such as the linear and quadratic shape effects, were not significant. Students' academic performance was not affected by the average academic performance of their mutually recognized socially close classmates, and there was no significant difference in academic performance among students with different numbers of mutually recognized socially close relationships. In the academic support relationship network, neither the in-degree performance effect nor the out-degree performance effect was significant, the other-effect of average academic performance did not exist, and the influence of gender on academic performance was not obvious (see Table 4). This indicates that there is no simple linear correlation between socially close relationships, academic support relationships, and academic performance. It may be because academic performance is jointly affected by a variety of complex factors, such as individual learning ability, learning methods, time invested in learning, etc., and the influence of social relationships is relatively small.

**Table 4.** Performance Influence Mechanisms Table

Effects	Explanation	Socially close relationships	Academic support relationships
<b>Selection network mechanism</b>			
Rate period performance	The rate at which students' weighted - grade - based performance (equivalent to GPA) changes over time.	1.54** (0.51)	1.56** (0.68)
Linear shape	The value representing the average performance level of students, serving as the intercept in the performance change model.	-1.62 (1.71)	-1.73 (1.66)
Quadratic shape	The degree of spread or variability in students' performance scores.	0.18 (0.32)	0.18 (0.32)
Performance Associated with Outdegree of Academic Support Relationships	The impact of the number of outgoing academic support relationships on students' performance. A positive value indicates a link to higher performance, a negative one the opposite.		0.06 (0.08)
Performance Associated with Indegree of Academic Support Relationships	The influence of incoming academic support relationship numbers on students' performance.		-0.09 (0.10)
Average performance alter	The impact of friends' average grades on a student's grade. Over time, their performance levels tend to converge.		0.98** (0.32)
Average performance reciprocated alters	The impact of reciprocal relationships on students' performance similarity. A reciprocal relationship may affect how similar their performances are.	1.21 (1.88)	
Reciprocated degree	The potential impact of reciprocal relationships on students' grades.	-0.18 (0.24)	-0.71** (1.21)
Gender	This variable is used to analyze whether there are differences in performance between genders.	-0.05 (0.11)	

Note: In social network analysis, 'Ego' is the relationship - initiator, 'Alter' the receiver. \*\* means  $P < 0.05$ ; results are significant when unrounded estimate/SE  $\geq 2$ . Both models had 5000 iterations, with a max convergence ratio of 0.18 for reliable estimation.

### 3.3.4 Post-hoc Analysis

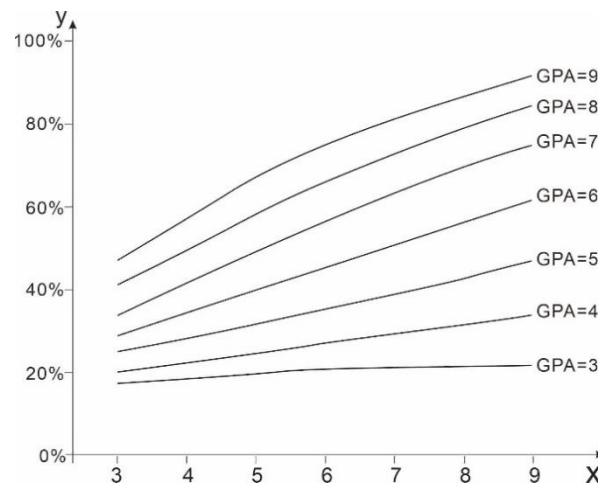
To further explore the influence mechanism of academic performance in the process of students' selection of socially close relationships and academic support relationships, this study conducted a post-hoc analysis. This analysis focused on the behavioral patterns of students at different academic performance levels when selecting social and academic support objects. By simulating the probability of students with an academic performance level of X choosing students with an academic performance level of Y, the potential patterns hidden behind the data were deeply explored.

This study adopted the post-hoc analysis method based on Ripley et al., and used log odds to simulate the dynamic influence of academic performance on relationship selection. Through this method, Figure 2 and Figure 3 were generated, which respectively showed the probability distribution of students when selecting socially close acquaintances and academic support providers.

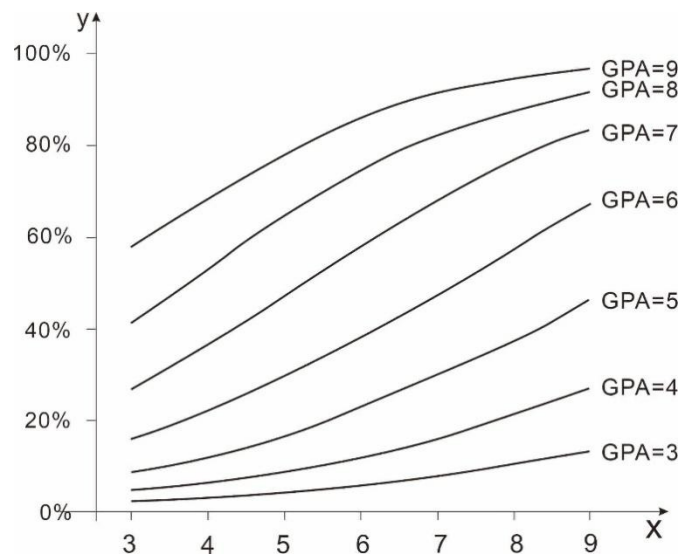
In terms of selecting socially close acquaintances (see Figure 2), except for students with extremely low academic performance, almost all students showed a tendency to be more inclined to establish socially close relationships with students with excellent academic performance. Moreover, the higher the academic performance of students, the more

proactive they were in selecting socially close acquaintances, and the greater the discrimination of their selected objects. This indicates that academic performance plays an important role in the construction of students' social relationships. Students with excellent academic performance are more attractive at the social level, and students attach great importance to academic ability when establishing socially close relationships.

In the selection of academic support relationships (see Figure 3), both students with lower and higher academic performance were more inclined to seek academic support from students with excellent academic performance. Students with higher academic performance were not only more proactive in initiating academic support relationships but also showed greater discrimination when selecting the objects to help. This reflects that when students seek academic support, they generally recognize the abilities of students with excellent academic performance and believe that they can provide more effective help.



**Figure 2.** Probability of Selecting Socially Close Peers Based on Students' GPA Levels. (The line represents the GPA of the selecting student, the x - axis shows the GPA of the selected student, the y-axis indicates the probability of selecting a student as a social close friend)



**Figure 3.** Probability of Selecting Academic Support Peers Based on Students' GPA Levels. (The line represents the GPA of the selecting student, the x - axis shows the GPA of the selected student, the y-axis indicates the probability of selecting a student as a social close friend)

Overall, the results of the post-hoc analysis fully demonstrate that academic performance has a significant impact on students' selection of socially close acquaintances and academic support providers. The attractiveness of students with excellent academic performance in social and academic support reflects students' emphasis on academic ability when constructing interpersonal relationships and academic support relationships. Students with lower academic performance may be aware of the potential value of establishing relationships with excellent students for their own improvement, while students with excellent academic performance, relying on their own abilities and willingness, are more selective in constructing social and academic support networks.

## 4 Discussion

### 4.1 Formation of Peer Networks in Cooperative Learning Groups

This study affirms that cooperative learning provides students—especially in the early stages—with a structured environment conducive to forming both socially close and academic support relationships. However, consistent with Berger & Dijkstra (2021), we found that such intra-group networks tend to weaken over time as students increasingly engage with peers outside their original learning groups. This raises the pedagogical implication that the benefits of cooperative group design may be time-limited without intentional scaffolding or sustained interaction opportunities. Unlike the assumption that cooperative learning inherently maintains cohesive peer dynamics (Johnson & Johnson, 2019), our findings suggest that peer cohesion requires continuous reinforcement.

### 4.2 Contradiction Between Peer Selection and Lack of Influence on GPA

One of the most striking findings is the clear asymmetry between peer selection mechanisms and influence outcomes. High-GPA students are frequently nominated as close peers and academic supporters, yet peer relationships themselves do not significantly enhance academic performance. This contradicts prevailing assumptions in social learning theory, which posit that social proximity fosters performance convergence (Wentzel et al., 2018). This discrepancy may reflect the short timespan of the study or the limited academic interdependence within middle school peer groups. Additionally, the strong selectivity of high-performing students—who tend to help only those they already know or trust—may restrict diffusion of academic benefit, reinforcing academic stratification rather than mitigating it. These findings underscore the importance of distinguishing between social preference and actual academic transmission mechanisms.

### 4.3 Network Stratification and Educational Equity Risks

Although homophily effects were not statistically significant, post-hoc analysis revealed that high-achieving students still tend to select other high achievers. This behavior pattern aligns with the "elite clustering" phenomenon described by González-Betancor et al. (2022), wherein high performers monopolize peer resources. In practice, this means that academically disadvantaged students may face both relational isolation and limited access to high-quality peer support. If not addressed, such network stratification may exacerbate existing educational inequalities. Educators should be cautious not to conflate visible participation with inclusive engagement. Interventions such as rotating peer roles, targeted mentoring, or structured academic support exchanges could help redistribute relational capital across the achievement spectrum.

### 4.4 Practical Implications and Theoretical Contributions

The findings of this study have several practical implications. First, group-based cooperative learning alone does not guarantee meaningful peer influence on academic outcomes. Without deliberate instructional strategies that promote cross-ability collaboration and mutual dependency, academically beneficial peer relationships may fail to materialize. Second, the study highlights the necessity of teaching students not only to seek help, but to do so effectively and inclusively. Finally, the gender disparities in relationship formation suggest a need for gender-sensitive network scaffolding. Theoretically, the study contributes by employing Stochastic Actor-Oriented Models (SAOMs) to disentangle peer selection and influence over time, offering empirical clarity to a domain often clouded by methodological limitations. It also challenges deterministic interpretations of social integration, suggesting that the presence of dense peer networks does not necessarily equate to academic advantage.

## 5. Conclusion

This study employed Stochastic Actor-Oriented Models (SAOMs) to explore the dynamic interplay between peer relationships (social closeness and academic support networks) and academic performance in Chinese middle school cooperative learning, addressing the gap in existing research on their reciprocal mechanisms. The key findings reveal that cooperative learning facilitates the initial formation of in-group relationships during the freshman year, but

out-group interactions increase over time. Notably, students with higher GPAs exhibit both greater popularity and proactivity in constructing social networks, demonstrating a pronounced selection bias where academic performance serves as a critical criterion for peer nomination. However, contrary to theoretical expectations, neither social closeness nor academic support relationships significantly influenced academic performance, indicating that selection processes dominate over influence effects in cooperative learning contexts. This challenges the assumption of social learning theory that peer interactions directly enhance academic outcomes, instead highlighting that peer dynamics primarily shape social structures rather than directly improving grades.

The research also uncovers an achievement-based differentiation in peer networks, which may exacerbate educational inequities, and gender-related structural disparities where female students are less frequently nominated for social or academic support. These findings offer theoretical insights by demonstrating the complex co-evolution of peer relationships and academic performance, emphasizing the need to integrate social network dynamics into educational interventions. Practically, educators should design structured peer interaction strategies (e.g., heterogeneous grouping and guided help-seeking mechanisms) to mitigate social stratification and promote inclusive learning environments.

The study's single-school sample and focus on student networks limit generalizability, as it excludes teacher-student interactions and off-campus relationships. Future research should expand network boundaries to include multiple educational stakeholders and contextual factors (e.g., teacher guidance, community resources). Additionally, integrating multi-dimensional learning outcomes (e.g., cognitive skills, emotional well-being) and adopting mixed-method approaches to explore students' motivational processes will deepen our understanding of how peer dynamics influence academic development in cooperative learning settings.

## References

- Ali, M., & Khan, N. (2020). Peer interaction patterns and student outcomes. *Teaching and Teacher Education*, 91, 42-55. <https://doi.org/10.1016/j.tate.2020.103046>
- Berger, J., & Dijkstra, J. K. (2021). Network evolution in classrooms: A longitudinal view. *Social Networks*, 65, 87-99. <https://doi.org/10.1016/j.socnet.2021.01.002>
- Boedien, L., van den Berg, R. M. A., & Kuyper, S. M. (2016). The effects of academic peer interaction on students' performance: Social interaction vs. social comparison. *Learning and Individual Differences*, 49, 296-304. <https://doi.org/10.1016/j.lindif.2016.06.015>
- Brown, B., Martin, T., & Garcia, J. (2021). Peer network influences on engagement and achievement. *Educational Studies*, 47(4), 451-470. <https://doi.org/10.1080/03055698.2019.1701010>
- Chen, X., & Zhang, Y. (2021). Self-regulated learning in cooperative settings. *Frontiers in Psychology*, 12, Article 734865. <https://doi.org/10.3389/fpsyg.2021.734865>
- Chen, Y. B., & Chang, W. H. (2022). Peer relationship quality and academic motivation: Mediating role of learning engagement. *Frontiers in Psychology*, 13, Article 851213. <https://doi.org/10.3389/fpsyg.2022.851213>
- Davis, R., Moore, L., & Taylor, M. (2020). Static vs dynamic peer networks and achievement. *Contemporary Educational Psychology*, 62, Article 101894. <https://doi.org/10.1016/j.cedpsych.2020.101894>
- Fang, H., & Xu, Q. (2021). Subject-specific peer support in middle school. *Social Psychology of Education*, 24, 883-902. <https://doi.org/10.1007/s11218-021-09621-5>
- Fernandez, E. (2021). Social dynamics and digital platforms in learning. *Computers & Education*, 161, 54-64. <https://doi.org/10.1016/j.compedu.2020.104028>
- Garcia, J., Lee, M., & Wu, C. (2021). Social learning communities and cooperative behavior in education. *Learning and Instruction*, 72, Article 101218. <https://doi.org/10.1016/j.learninstruc.2020.101218>
- Gillies, R. M. (2019). Cooperative learning: Review of research and practice. *Australian Journal of Teacher Education*, 44(3), 1-19. <https://doi.org/10.14221/ajte.2019v44n3.1>
- González-Betancor, M. E., López-Puig, C., & Cebrián-Martínez, D. C. (2022). The effect of cooperative learning on academic performance: Evidence from a randomized experiment. *Assessment & Evaluation in Higher Education*, 47(1), 57-70. <https://doi.org/10.1080/02602938.2020.1853890>
- Hmelo-Silver, C., & Chinn, C. A. (2020). Collaborative learning and the co-construction of knowledge. *Educational Psychologist*, 55(3), 144-157. <https://doi.org/10.1080/00461520.2020.1765063>

- Johnson, D. W., & Johnson, R. T. (2019). Cooperative learning: The foundation for active learning. In M. Orey (Ed.), *Active learning beyond future* (pp. 17-28). Springer. [https://doi.org/10.1007/978-981-13-2489-4\\_2](https://doi.org/10.1007/978-981-13-2489-4_2)
- Laal, M., & Ghodsi, S. (2019). Benefits of collaborative learning. *Procedia - Social and Behavioral Sciences*, 230, 336-341. <https://doi.org/10.1016/j.sbspro.2011.10.067>
- Lee, S., & Kim, H. (2020). Cooperative reading strategies and comprehension achievement. *Asia-Pacific Education Researcher*, 29, 89-97. <https://doi.org/10.1007/s40299-019-00458-w>
- Liu, C., & Zhao, D. (2020). Peer nomination reliability and network analysis. *Computers in Human Behavior*, 109, 30-38. <https://doi.org/10.1016/j.chb.2020.106354>
- Liu, F., & Huang, Y. (2021). Improving group work through peer dynamics. *Educational Review*, 73(6), 714-730. <https://doi.org/10.1080/00131911.2020.1732889>
- Martínez, S., & López, E. (2019). Social selection and academic centrality. *Learning and Individual Differences*, 70, 36-47. <https://doi.org/10.1016/j.lindif.2019.01.004>
- Ripley, R., Snijders, T., & Boda, A. (2020). Introduction to stochastic actor-oriented models using RSiena. *Network Science*, 8(4), 442-457. <https://doi.org/10.1017/nws.2020.26>
- Rossi, F. (2021). Network modeling in educational contexts. *Social Science Computer Review*, 39(1), 105-121. <https://doi.org/10.1177/0894439320911612>
- Smith, B., Williams, A., & Clark, J. (2020). Academic help-seeking and peer networks: Linking social integration to achievement. *Journal of Educational Psychology*, 112(7), 1307-1320. <https://doi.org/10.1037/edu0000425>
- Snijders, T., & Koskinen, J. (2021). Social network dynamics in educational contexts: Understanding selection and influence. *Annual Review of Sociology*, 47, 381-400. <https://doi.org/10.1146/annurev-soc-092420-012336>
- Wang, J., Ma, R., & Zhang, Y. (2021). Longitudinal effects of peer support on academic achievement through school belonging and engagement. *Journal of Adolescence*, 88, 1-9. <https://doi.org/10.1016/j.adolescence.2020.12.003>
- Wang, X., & Liu, Y. (2021). Critical thinking and cooperative learning: A quasi-experimental study. *Thinking Skills and Creativity*, 41, Article 100854. <https://doi.org/10.1016/j.tsc.2021.100854>
- Wentzel, K. A., Jablansky, G. J., & Muenks, D. (2018). Peer social acceptance and academic achievement: A meta-analytic study. *Educational Psychology Review*, 30(2), 337-369. <https://doi.org/10.1007/s10648-017-9434-2>
- Wilson, B. (2020). Social media influence on adolescent learning. *Journal of Adolescent Research*, 35(2), 220-240. <https://doi.org/10.1177/0743558419878264>
- Yamamoto, T. (2020). Performance polarization in student networks. *Journal of Educational Data Mining*, 12(3), 92-109. <https://doi.org/10.5281/zenodo.4068522>
- Yang, Y., & Li, J. (2022). Academic influence in dynamic peer networks. *Educational Research and Evaluation*, 28(3-4), 174-196. <https://doi.org/10.1080/13803611.2022.2074238>
- Zhao, Z., & Sun, M. (2022). Fostering autonomous learning in Chinese secondary schools. *Educational Research for Policy and Practice*, 21(1), 77-95. <https://doi.org/10.1007/s10671-021-09313-7>
- Zhou, H., & Wu, L. (2020). Team-based learning in secondary education. *Journal of Education and Learning*, 9(2), 112-120. <https://doi.org/10.5539/jel.v9n2p112>

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