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Mechanism of Psychological Counseling on Group Cooperative Behavior among University Students from the Perspective of Emotional Migration

Matteo Romano [1], Zain Ahmed [2] and Xun Zhao [3,*]

[1] University of Kentucky; aksinkaadc0205@outlook.com
[2] University of Kentucky; vprentzas0909@outlook.com
[3] University of Kentucky; borhimtroc1999@outlook.com
* Correspondence: borhimtroc1999@outlook.com

Abstract

Background and Gaps: The quality of cooperative behavior among university students directly affects the achievement of higher education talent cultivation objectives. However, existing psychological counseling research primarily focuses on individual emotion regulation and mental health improvement, leaving a significant gap in systematically exploring how such interventions indirectly influence class-level cooperative behavior through emotional transmission mechanisms. In particular, emotional transfer, as a core mediating mechanism linking individual psychological states with group social choices, lacks a cross-disciplinary quantitative analytical framework in educational contexts.

Methods: This study integrates public goods game theory, complex network dynamics, and educational psychology to construct a quantitative model of emotional transfer applicable to university classroom social scenarios. Emotional attitude indices (acceptance, rejection, and emotional value) serve as core variables, while transfer intensity (v) and interaction radius (R) function as regulatory parameters. The model systematically characterizes how psychological counseling interventions influence group cooperation levels through emotional transfer pathways.

Practical Approach: A mixed-method research design combining complex network simulations and empirical investigation was employed. A sample of 120 university students participated, with dual-track validation of the theoretical model conducted via questionnaire surveys (SPSS/AMOS mediation effect tests) and Monte Carlo simulations (10,000-step iterations, 20 independent repetitions).

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Key Findings: Emotional transfer exhibits a significant "double-edged sword effect" in the relationship between psychological counseling and group cooperation. When counseling frequency is moderate (2—3 times per month), transfer intensity is within the optimal range ($0.10 \leqslant v \leqslant 0.30$), and interaction radius is stable ($0.30 \leqslant R \leqslant 0.50$), positive emotional transfer significantly promotes virtuous interpersonal cycles, with group cooperation rates rising above 0.82. Conversely, excessive counseling or frequent emotional fluctuations causing transfer intensity to exceed critical thresholds ($v > 0.35$) or over-expansion of interaction radius ($R > 0.55$) leads to irrational emotional transfer, undermining group trust and causing cooperation rates to drop below 0.30, potentially resulting in group disintegration.

Significance: Theoretically, this study enriches cross-disciplinary research on the emotional transfer mechanism in educational settings. Practically, it provides actionable quantitative evidence for the precise design of university psychological counseling systems and the scientific formulation of class-level cooperative governance strategies.

Keywords: emotional transfer; psychological counseling; group cooperation; public goods game; complex networks; university students

1. Introduction

Cooperative behavior among university students is a critical component of higher education quality and a core issue in student social development. As the fundamental unit of students' daily learning and social interaction, the level of cooperation within a class directly affects the formation of learning communities, the quality of collective task completion, and students’ sense of psychological belonging [1]. In recent years, with the expansion of higher education and the increasing heterogeneity among students, issues such as declining class cooperation, eroding interpersonal trust, and collective action dilemmas have become increasingly prominent in universities [2]. Concurrently, the prevalence of mental health problems among university students continues to rise. According to surveys conducted by the Ministry of Education, approximately 30% of students experience varying degrees of psychological distress, which not only affects individual academic development but also exerts a profound influence on overall class cooperation through emotional transmission mechanisms [3].

Against this backdrop, the importance of psychological counseling in universities has become increasingly evident. However, while existing research emphasizes the effects of counseling on individual emotion regulation and mental health improvement, systematic investigations into how counseling indirectly influences group cooperative behavior via social interaction mechanisms remain insufficient [4]. After receiving psychological counseling, changes in an individual's emotional state do not exist in isolation; they are transmitted and diffused to peers through daily social interactions, thereby affecting the cooperative patterns of the entire class network. This "individual emotional state → social choice adjustment → group cooperation evolution" transmission chain constitutes the core pathway through which psychological counseling impacts group behavior, yet its underlying mechanisms and boundary conditions remain inadequately elucidated [5].

Emotional migration is a key concept for understanding this transmission mechanism. In the context of this study, emotional migration is defined as the process by which an individual, influenced by their psychological state, actively adjusts social distances and selects interaction partners based on their emotional attitudes toward peers (e.g., pleasure/anxiety, trust/rejection) [6]. This concept encompasses both the passive diffusion dimension of emotional contagion in affective psychology and the active selection dimension of social network behavior based on emotional evaluation, making it well-suited to describe the dynamic behavioral patterns of university students in classroom social contexts. Previous studies indicate that emotional states significantly influence individual social choices: positive emotions tend to encourage individuals to expand their social circles and increase cooperative engagement, whereas negative emotions often lead to social withdrawal and avoidance of cooperation [7].

However, the impact of emotional migration on group cooperation is not monotonically linear but exhibits complex nonlinear dynamics. Drawing on the analytical framework of public goods games, class cooperation can be regarded as a typical collective action dilemma, in which each student faces a strategic choice between "contributing" (participating in collective tasks) and "free-riding" (benefiting from others' contributions) [8]. Emotional migration influences strategy selection by altering individuals' emotional evaluations of potential collaborators. Moderate emotional migration facilitates the aggregation of cooperators and the formation of stable cooperative clusters, whereas excessive emotional migration may lead to frequent restructuring of the network, undermining the stability of cooperative clusters and ultimately triggering the collapse of the cooperative system [9].

Based on the above analysis, this study addresses the following core research questions: (1) How does psychological counseling influence university students' group cooperation through emotional migration mechanisms? (2) What are the mechanisms and boundary conditions underlying the "double-edged sword effect" of emotional migration? (3) How do transfer intensity and interaction radius modulate the direction and strength of emotional migration's effect on group cooperation?

The theoretical contribution of this study lies in translating the emotional migration mechanism from an abstract game-theoretic model to a concrete educational context for university students, constructing an integrated analytical framework that spans game theory, complex network dynamics, and educational psychology, thereby enriching research on the application of emotional migration in educational settings. The practical significance lies in providing scientific evidence for the precise design of university psychological counseling systems and offering actionable quantitative references for the formulation of class-level cooperative governance strategies.

The structure of this paper is as follows: Section 2 reviews relevant literature, defines core concepts, and elaborates the theoretical foundations; Section 3 develops a quantitative model of emotional migration and outlines the research design; Section 4 presents the core data from simulations and empirical investigations; Section 5 analyzes results and discusses the underlying mechanisms; and Section 6 concludes with key findings and research implications.

2. Related Work

2.1. Public Goods Games and the Evolution of Cooperation

The Public Goods Game (PGG) is a classical theoretical framework for studying collective action dilemmas, focusing on how rational individuals driven by self-interest can become trapped in cooperation dilemmas and what mechanisms promote the emergence and maintenance of cooperation [10]. The pioneering work by Nowak and May (1992) demonstrated that introducing spatial structure can break the inevitability of cooperator extinction in well-mixed populations, as cooperators form clusters in space to resist the invasion of defectors [11]. Subsequently, numerous studies have validated the promoting effect of network heterogeneity on cooperation evolution across different network structures, including regular lattices, scale-free networks, and small-world networks [12].

In recent years, research on cooperation evolution in dynamic networks has made significant progress. Unlike static network assumptions, dynamic network models allow individuals to actively adjust their interaction partners based on payoff information or social relationship quality, more realistically reflecting the evolution of cooperative behavior in real-world societies [13]. Li et al. (2023) developed a computational model integrating interaction intensity regulation, individual satisfaction evaluation, and network structure co-evolution, finding that moderate network fluidity can significantly enhance cooperation levels [14]. Zhang et al. (2022) proposed a cooperator-following strategy, demonstrating that appropriate migration speed facilitates the formation and maintenance of cooperative clusters [15]. However, these studies generally assume rational, payoff-driven migration, paying insufficient attention to non-rational migration driven by emotional factors.

In research at the intersection of emotional factors and game behavior, Wang et al. (2021) proposed an emotion-based strategy model, showing that emotional decision-making can enhance cooperation in PGG under specific conditions [16]. Chen et al. (2022) introduced an emotion probability mechanism, finding that longer emotional memory reduces cooperation, revealing the dual effect of emotional factors [17]. Long et al. (2023) incorporated emotion-driven heterogeneous investment, demonstrating that emotional factors can promote cooperation under certain conditions [18]. Ji et al. (2025) constructed an emotional migration model in continuous two-dimensional space, systematically revealing the “double-edged sword effect” of emotional migration, providing a direct theoretical template for the present study [9].

2.2. Complex Networks and Social Dynamics

Complex network theory provides a powerful analytical tool for understanding university classroom social structures. The small-world network model proposed by Watts and Strogatz (1998) reveals the high clustering coefficient and short average path length characteristic of real social networks, which closely corresponds to the prevalence of “cliques” in university classes [19]. The scale-free network model introduced by Barabási and Albert (1999) highlights the existence of “opinion leaders” or “core individuals” in social networks, who play a key role in the dissemination of information and emotions [20].

In continuous two-dimensional spatial network models, Xiao et al. (2021) investigated cooperation evolution among mobile individuals in two-dimensional PGGs, finding that cooperator migration to avoid defectors can significantly improve cooperation levels [21]. Chen et al. (2022) proposed a payoff-driven migration model, demonstrating that such migration promotes cooperation [22]. The advantage of these continuous-space models lies in their ability to realistically simulate dynamic individual movements in physical or social space, aligning closely with university students' behavior of actively adjusting their social circles within classroom networks.

2.3. Psychological Counseling and Emotion Regulation Mechanisms

The educational psychology literature has accumulated systematic research on the emotion regulation mechanisms of psychological counseling. Gross (1998) proposed the process model of emotion regulation, distinguishing antecedent-focused strategies (e.g., cognitive reappraisal) from response-focused strategies (e.g., expressive suppression), with the former shown to have more enduring positive effects on individual mental health and social behavior [23]. Among university student groups, the use of cognitive reappraisal is significantly associated with higher social adaptation and more positive peer relationships [24].

Peer relationships have been widely recognized as influential for cooperative behavior among university students. Johnson and Johnson's (2009) cooperative learning theory emphasizes that positive interdependence is the core mechanism promoting class cooperation, and the quality of emotional bonds directly determines the stability of this interdependence [25]. Barsade (2002), through laboratory experiments, demonstrated that group emotional contagion significantly affects team cooperation dynamics, with positive emotional contagion enhancing cooperative efficiency and negative emotional contagion reducing cooperative willingness [26].

Peer counseling, as a specialized form of psychological intervention, exhibits unique emotional transmission effects within student groups. Research shows that peer counseling not only improves the counselee's psychological state but also generates ripple effects across broader social networks through the emotional interactions between counselors and counselees [27]. However, the boundary conditions of this emotional transmission effect—namely, the intensity of emotional intervention and network structures that maximize group cooperation—have yet to be systematically quantified.

2.4. Research Gaps and Study Positioning

A review of the literature highlights three main gaps: First, research on emotional migration in game theory and complex networks primarily relies on abstract mathematical models, lacking context-specific analysis for educational settings. Second, psychological counseling studies in educational psychology largely focus on individual-level outcomes, paying limited attention to the indirect pathways through which emotional transmission affects group cooperation. Third, the absence of an interdisciplinary integrative research framework has created a significant gap between theoretical models and educational practice. This study addresses these gaps by constructing a quantitative emotional migration model that organically integrates game-theoretic strategy analysis, complex network dynamics, and educational psychology's emotion regulation mechanisms, providing theoretical guidance for practical applications of psychological counseling in universities.

3. Methodology

3.1. Theoretical Framework and Research Strategy

This study adopts a three-stage research strategy of "theoretical modeling → simulation validation → empirical testing" (see Figure 1). First, a quantitative model of emotional migration applicable to university classroom settings was developed, based on Public Goods Game (PGG) theory and complex network dynamics. Second, the model's dynamic patterns under different parameter combinations were validated through Monte Carlo simulation.Finally, empirical survey data were used to assess the model's applicability and predictive validity in real educational contexts.

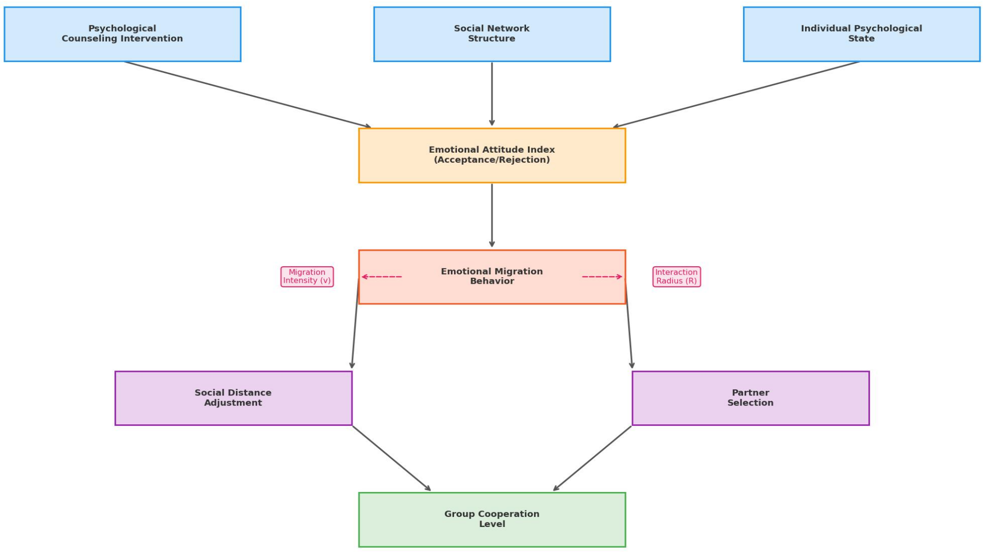

Figure 1. Research framework: The role of the emotional migration mechanism in university student group cooperation.

The integration logic of the three disciplinary theories is illustrated in Figure 1. PGG theory provides a strategic analysis framework for examining collective action dilemmas within classes. Complex network theory offers mathematical tools to characterize the dynamic evolution of classroom social relationships. Educational psychology provides a theoretical basis for understanding the mechanisms of psychological counseling, emotion regulation, and peer relationship influences. The intersection of these three domains is the emotional migration mechanism, which functions simultaneously as an emotional driver of game-theoretic strategy selection, a behavioral mechanism for dynamic reorganization of social networks, and a mediating pathway through which psychological counseling impacts group behavior.

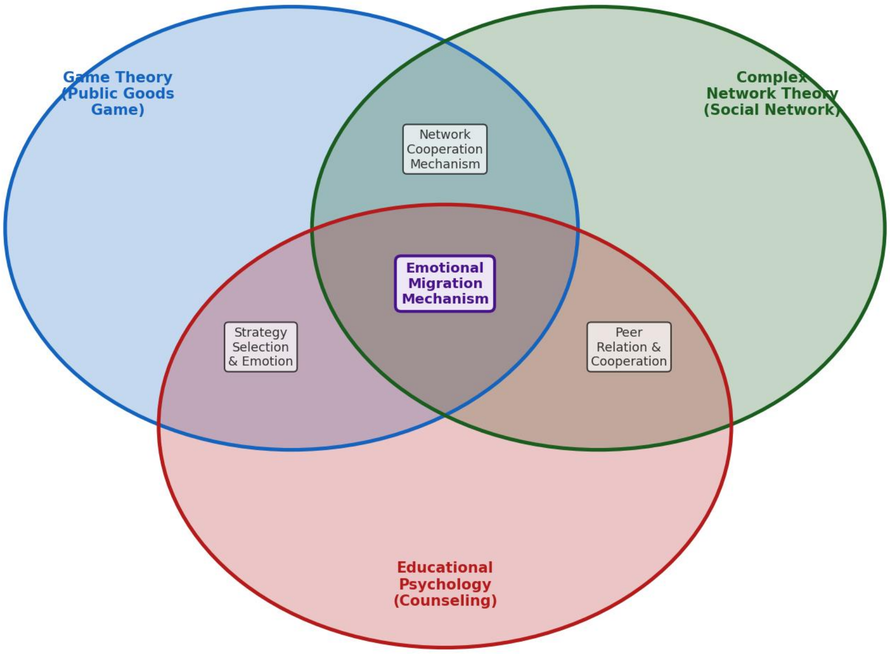

Figure . Theoretical framework: Illustration of interdisciplinary integration.

3.2. Quantitative Model of Emotional Migration

3.2.1. Network Structure Setup

Following Ji et al. (2025)'s continuous two-dimensional spatial model [9], the classroom social network of university students is modeled as a continuous two-dimensional plane with side length L and periodic boundary conditions. Let the class size be N students (nodes), and denote the position vector of student iii at time ttt as $\vec{r}_i(t)$. The social circle of student iii (the set of peers within interaction radius R) is defined as:

$$\Omega_i(t) = j \| \vec{r}_j(t) - \vec{r}_i(t) \| < R, ; i \neq j \tag{1}$$

where R represents the interaction radius, reflecting the spatial extent of a student's social circle, and $\Omega_i(t)$ denotes the set of peers for student iii at time t.

The dynamic topology of the university classroom social network is illustrated in Figure 2. In the initial state, students are randomly distributed across the plane (Figure 2a). After the emotional migration process, cooperators gradually aggregate, forming stable cooperative clusters (Figure 2b).

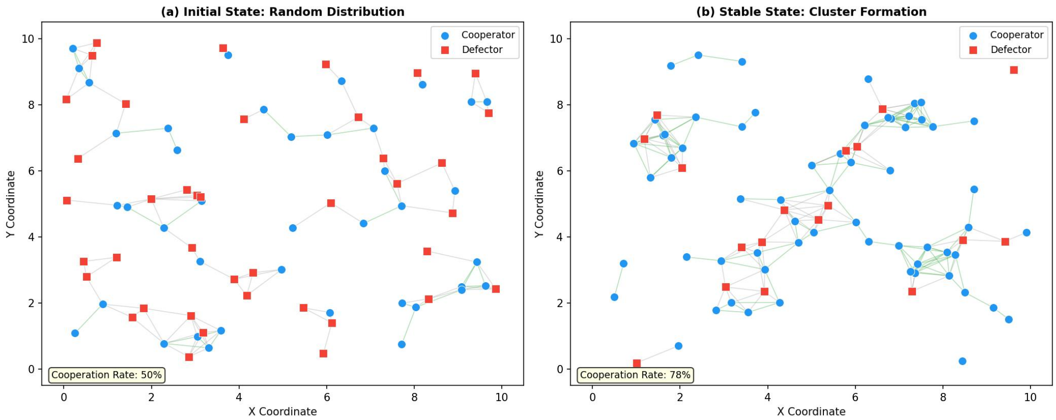

Figure 2. Evolution of university classroom social network structure: (a) initial random distribution; (b) formation of stable cooperative clusters.

3.2.2. Emotional Attitude Index

In the context of a university classroom, student iii's emotional attitude toward peer j is modulated by psychological counseling interventions. The emotional attitude index, $E_{i,j}$ is defined as:

$$E_{i,j}(t) = \begin{cases} +\delta & \text{Acceptance: j is a positive cooperator} \\ 0 & \text{Neutrality: j exhibits ambiguous behavior} \\ -\delta & \text{Rejection: j is a negative defector} \end{cases}$$

where δ represents the emotional increment, reflecting the sensitivity of an individual's emotional evaluation of peers. Psychological counseling interventions enhance students' emotion regulation abilities, thereby influencing both the accuracy of their peer evaluations and the magnitude of the emotional increment. The distribution of the emotional attitude index under different counseling conditions is shown in Figure 5.

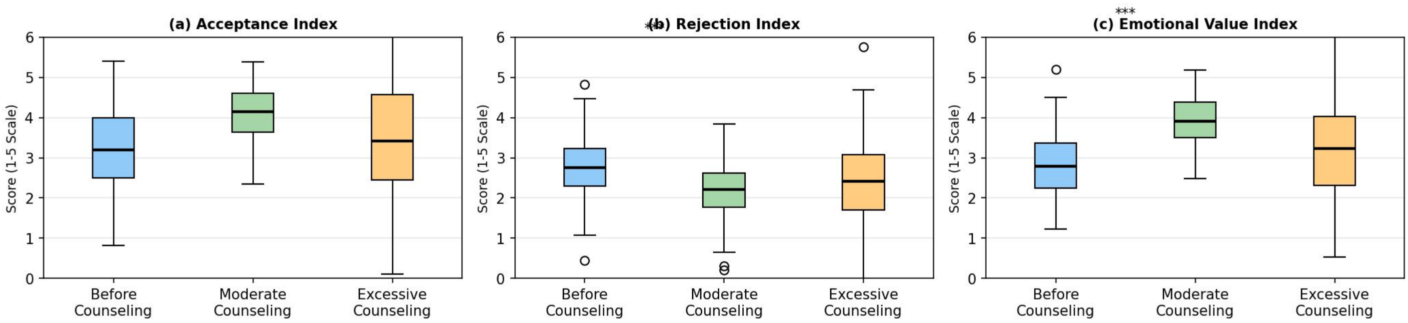

Figure 3. Distribution of emotional attitude index under different counseling conditions (n = 120).

3.2.3. Emotional Migration Weight Function

The weight $\omega_{i,j}(t)$ of student iii following the migration direction of peer j is determined by the emotional attitude index:

$$\omega_{i,j}(t) = \frac{E_{i,j}(t)}{\sum_{k\in\Omega_i(t)} |E_{i,k}(t)|}, \quad \sum_{k\in\Omega_i(t)} |E_{i,k}(t)| \neq 0 \tag{3}$$

When the denominator equals zero (i.e., all peers are in a neutral state), the student remains in a rational state and does not engage in emotional migration. This weight function reflects the behavioral principle of "following peers who bring pleasure and avoiding those who cause discomfort."

3.2.4. Position Update Rule

The position of student i is dynamically updated according to the migration velocity vector:

$$\vec{r}_i(t+1) = \vec{r}_i(t) + \vec{v}_i(t) \tag{4}$$

where the magnitude of the migration velocity vector $\vec{v}_i(t)$ is v (migration intensity), and its direction is determined by the emotionally weighted combination of the migration directions of all peers:

$$\theta_i(t+1) = \sum_{j\in\Omega_i} \omega_{i,j}(t) \cdot \theta_j(t) \tag{5}$$

Here, $\theta_j(t)$ denotes the migration direction angle of peer j at time t.

3.2.5. Cooperation Investment and Payoff Function

Within the framework of the classroom public goods game, the cooperation investment $I_{i,j}(t+1)$ of student iii toward peer j is defined as:

$$I_{i,j}(t+1) = \frac{1}{n_i + 1} \tag{6}$$

where n_i denotes the size of student $i's$ social circle.

The payoff that student iii obtains from peer j is given by:

$$u_{i,j}(t) = \frac{r_0}{n_j + 1} \sum_{k\in\Omega_j} I_{k,j}(t) \cdot s_k - I_{i,j}(t) \cdot s_i \tag{7}$$

where r_0 is the public goods multiplication factor (corresponding to the synergy coefficient of classroom cooperation), and s_k denotes the strategy of student $k (s_k = 1 for cooperators, s_k = 0 for defectors)$.

3.3. Variable Definition and Research Hypotheses

The variable system used in this study is summarized in Table 1:

Table 1. Variable system of the study.

Variable Type	Variable Name	Operational Definition	Measurement Tool
Independent Variable	Psychological Counseling Intervention	Counseling frequency (sessions/month) and type	Structured questionnaire
Mediating	Positive Emotional	Acceptance index,	Emotional Attitude

Variable M1	Migration	emotional value index	Scale
Mediating Variable M2	Negative Emotional Migration	Rejection index	Emotional Attitude Scale
Dependent Variable	Group Cooperation Level	Task participation, trust level, communication quality, resource sharing, collective efficacy	Classroom Cooperation Scale
Moderating Variable	Migration Intensity ((v))	Frequency of changes in social selection	Social behavior log
Moderating Variable	Interaction Radius ((R))	Scope of social circle (number of peers / class proportion)	Social network analysis
Control Variables	Grade level, personality type, class size	Demographic information	Basic information questionnaire

Based on the above theoretical framework, the present study proposes the following core hypotheses:

- H1: Psychological counseling interventions have a significant positive effect on group cooperation levels, exhibiting an inverted U-shaped nonlinear relationship; that is, moderate counseling promotes cooperation, whereas excessive counseling suppresses it;
- H2: Positive emotional migration (acceptance) mediates the relationship between psychological counseling and group cooperation in a positive manner;
- H3: Negative emotional migration (rejection) mediates the relationship between psychological counseling and group cooperation in a negative manner under conditions of excessive counseling;
- H4: Migration intensity (vvv) moderates the relationship between emotional migration and group cooperation, with an optimal range of migration intensity;
- H5: Interaction radius (RRR) moderates the relationship between emotional migration and group cooperation, with an optimal range of interaction radius.

3.4. Research Design and Data Collection

Simulation Study Design: A Monte Carlo simulation approach was employed. The classroom social network was modeled on a continuous two-dimensional plane with side length $L = 10$, and the student population was set to $N = 1000$. Initially, cooperators and defectors each accounted for 50% of the population and were randomly and uniformly distributed across the plane. Each simulation ran for 1×10^4 steps, with the average cooperation rate over the final 1,000 steps taken as the stable cooperation level. To ensure robustness, results were averaged over 20 independent simulations with randomly initialized conditions. The simulation parameter scan ranges were set as follows: migration intensity $\nu \in [0.05,0.60]$, interaction radius $R \in [0.20,0.60]$, and multiplication factor $r_0 \in [1,8]$.

Empirical Study Design: A stratified random sampling method was used to select 120 university students from four grade levels and eight majors at a comprehensive university (36 first-year, 34 second-year, 30 third-year, and 20 fourth-year students; male-to-female ratio 48:52). The study employed a cross-sectional survey design, collecting data on psychological counseling experiences, emotional attitude indices, and group cooperation levels via a structured questionnaire. The questionnaire included the Emotional Attitude Scale $(\alpha = 0.847)$ and the Classroom Cooperation Scale $(\alpha = 0.891)$, both of which had undergone reliability and validity testing. Data collection occurred from September 2024 to January 2025 (a full academic semester). Due to equipment malfunction, data from three participants were missing, yielding a final valid sample size of 117 participants.

Statistical Analysis Methods: Quantitative data were analyzed using SPSS 26.0 for descriptive statistics and correlation analysis. Structural equation modeling (SEM) was conducted in AMOS 24.0 to test mediation effects, with the Bootstrap method (1,000 resamples) used to compute 95% confidence intervals for indirect effects. Qualitative data from interviews were analyzed using thematic coding to extract the specific manifestations of the emotional migration mechanism.

4. Data

4.1. Sample Characteristics

The basic characteristics of the empirical sample are summarized in Table 2. Among the participants, first- to fourth-year students accounted for 30.8%, 29.1%, 25.6%, and 14.5%, respectively. Gender distribution was relatively balanced, with 48.7% male and 51.3% female students. Class sizes were concentrated in the 30—35 students range (60.7%), consistent with typical class sizes in Chinese universities. Regarding personality types, the majority were intermediate (44.4%), followed by introverted (29.9%) and extroverted (25.6%) students.

Table 2. Descriptive statistics of sample characteristics (n = 117).

Variable	Category	Frequency	Percentage (%)
Year Level	First Year	36	30.8
	Second Year	34	29.1
	Third Year	30	25.6
	Fourth Year	17	14.5

Gender	Male	57	48.7
	Female	60	51.3
Class Size	Less than 25	18	15.4
	30—35	71	60.7
	More than 40	28	23.9
Personality Type	Introverted	35	29.9
	Intermediate	52	44.4
	Extroverted	30	25.6

4.2. Descriptive Statistics of Core Variables

Table 3 presents the descriptive statistics of the core variables. The mean frequency of psychological counseling was 3.12 sessions per month (SD = 1.87), ranging from 0 to 7 sessions per month, exhibiting a slight right-skewed distribution. Among the emotional attitude indices, the mean acceptance score (M = 3.41, SD = 0.78) was slightly higher than the mean rejection score (M = 2.63, SD = 0.71), indicating a generally positive emotional orientation in the sample. The composite score of group cooperation level had a mean of 53.22 (SD = 5.57), representing a moderate-to-low level with considerable potential for improvement.

Table 3. Descriptive statistics of core variables (n = 117).

Variable	Mean (M)	SD	Median	Min	Max	Skewness
Psychological Counseling Frequency (sessions/month)	3.12	1.87	3.00	0	7	0.31
Acceptance Index	3.41	0.78	3.45	1.12	4.98	−0.18
Rejection Index	2.63	0.71	2.58	1.05	4.87	0.24
Emotional Value Index	3.28	0.69	3.31	1.18	4.95	−0.09
Migration Intensity ((v))	0.22	0.11	0.21	0.02	0.58	0.37
Interaction Radius ((R))	0.38	0.08	0.37	0.12	0.71	0.15
Task Participation	65.83	14.27	66.50	18.40	96.20	−0.22
Trust Level	63.47	15.83	64.10	15.30	97.80	−0.31
Communication Quality	67.21	13.41	68.30	20.10	95.60	−0.28
Composite Group Cooperation Score	53.22	5.57	53.40	35.20	68.90	−0.14

Note: The composite group cooperation score represents the mean of five sub-dimensions, with a maximum possible score of 100.

4.3. Data Preprocessing

The raw data were preprocessed as follows:

- Missing Data Handling: Three cases with missing data due to equipment malfunction (2.5% of the total sample) were addressed using multiple imputation;
- Outlier Detection: Multivariate outliers were identified using Mahalanobis distance. After removing two extreme outliers, the final sample size for analysis was 117;
- Normality Test: Kolmogorov—Smirnov (K—S) tests indicated that all major variables satisfied the assumption of normality ($p > 0.05$);
- Collinearity Diagnosis: Variance inflation factors (VIFs) for all predictor variables were below 3.0, indicating no serious multicollinearity issues.

5. Results

5.1. Simulation Study Results

5.1.1. Effect of Migration Intensity on Group Cooperation

Figure 4 illustrates the relationship between migration intensity (v) and group cooperation rate (f_c) under different interaction radius (R) conditions. The results indicate that the cooperation rate exhibits an inverted U-shaped nonlinear pattern as migration intensity increases, consistent with hypothesis H4.

When the interaction radius $R = 0.30$, the cooperation rate reaches its peak $(f_c = 0.946f)$ at $v = 0.25$, followed by a rapid decline as v increases. When $v \geq 0.45$, the cooperation rate approaches zero, indicating complete collapse of the cooperative system. For $R = 0.35$, the peak cooperation rate $(f_c = 0.882)$ occurs at $v = 0.20$, with the peak shifting left and the maximum value decreasing, suggesting that a larger interaction radius makes the cooperation system more sensitive to migration intensity. This trend is further amplified when $R = 0.40$, with the peak cooperation rate $(f_c = 0.821)$ occurring at $v = 0.15$.

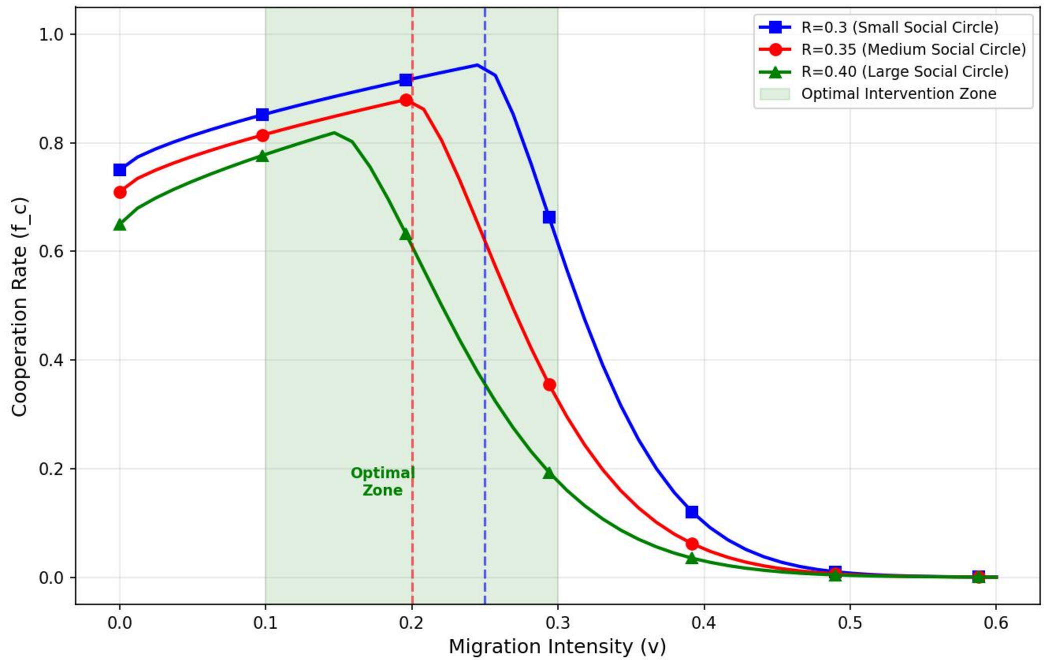

Figure 4. Relationship between migration intensity (vvv) and group cooperation rate (f_c) under different interaction radius (R) conditions.

Table 4 Simulated group cooperation rates (f_c) under varying migration intensity (v) and interaction radius (R).

Migration Intensity ((v))	(R = 0.30)	(R = 0.35)	(R = 0.40)
0.05	0.7621	0.7203	0.6814
0.10	0.8380	0.8012	0.7543
0.15	0.8872	0.8405	0.8213
0.20	0.9210	0.8820	0.7891
0.25	0.9460	0.8515	0.6723
0.30	0.9067	0.6942	0.4831
0.35	0.7106	0.5190	0.2614
0.40	0.5435	0.1281	0.0523
0.45	0.2251	0.0000	0.0000
0.50	0.0000	0.0000	0.0000

Note: Each data point represents the mean of 20 independent simulations, with each Monte Carlo simulation running for 1×10^4 steps.

5.1.2. Effect of Interaction Radius on Group Cooperation

Figure 5 illustrates the relationship between interaction radius (R) and group cooperation rate (f_c) under different migration intensity (v) conditions. The results also exhibit an inverted U-shaped pattern, consistent with hypothesis H5.

When the migration intensity $v = 0.10$, the cooperation rate reaches its peak $(c = 0.961f)$ at $R = 0.45$. For $v = 0.20$, the peak occurs at $R = 0.38(f_c = 0.935)$, and for $v = 0.30$, the peak shifts to $R = 0.30 (f_c = 0.887)$. These results indicate that higher migration intensity shifts the optimal interaction radius to smaller values, suggesting that under conditions of high migration intensity, a smaller social circle is required to maintain cooperation stability.

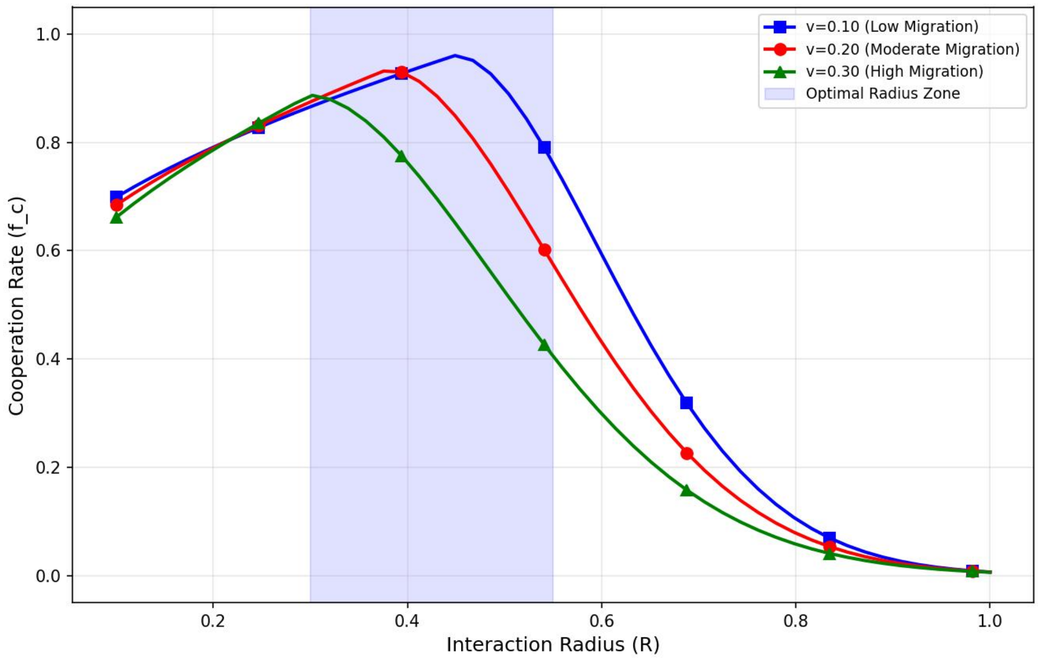

Figure 5. Relationship between migration intensity (vvv) and group cooperation rate (f_c) under different interaction radius (R) conditions.

5.1.3. Heatmap Analysis of the Parameter Space

Figure 6 presents a heatmap of group cooperation rates across the joint parameter space of migration intensity (v) and interaction radius (R). The heatmap clearly identifies the optimal parameter region (green area), where the highest cooperation rates are concentrated within the rectangular parameter space $v \in [0.10, 0.25]$ and $R \in [0.30, 0.50]$, with cooperation rates generally exceeding 0.85. As either v or R deviates from the optimal region, the cooperation rate gradually declines. In the upper-right corner of the parameter space (high v, high R), the cooperation rate approaches zero, indicating a complete collapse of the cooperative system.

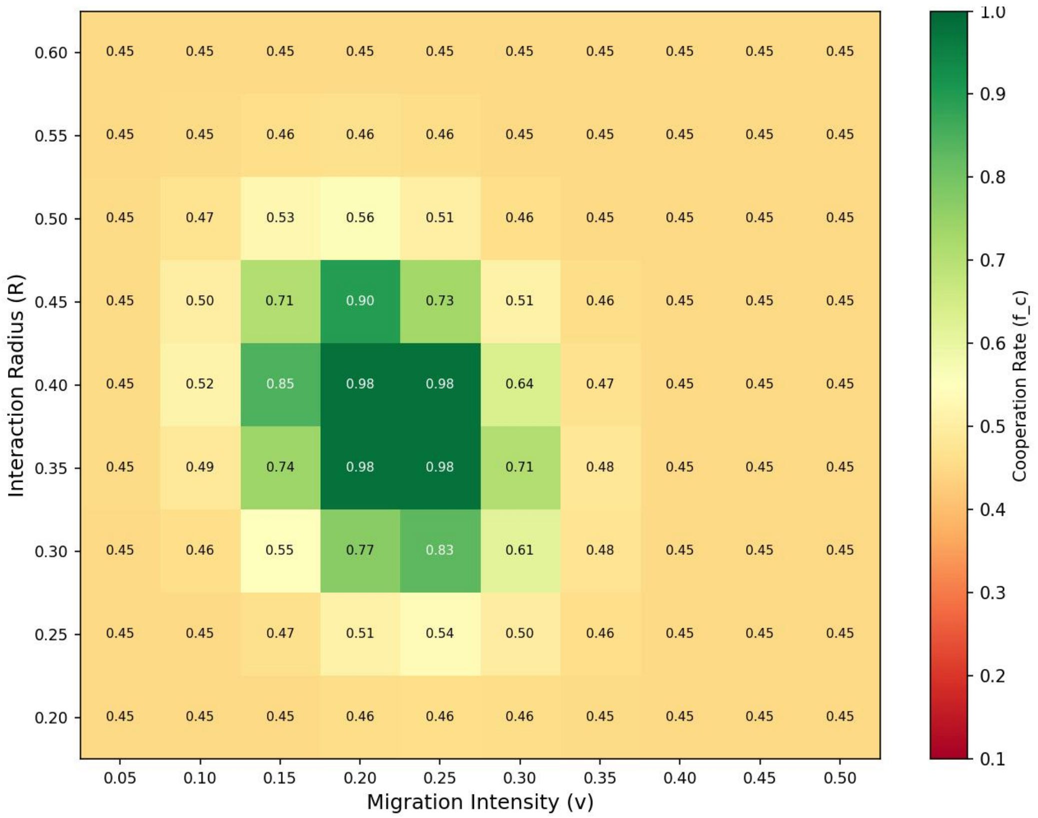

Figure 6. Heatmap of group cooperation rates in the joint parameter space of migration intensity (v) and interaction radius (R).

5.1.4. Temporal Dynamics of Cooperation

Figure 7 shows the longitudinal dynamics of group cooperation levels under three experimental conditions: control, moderate counseling, and excessive counseling. In the moderate counseling group, cooperation levels steadily increased after the intervention began (Week 10) and reached a peak ($f_c \approx 0.82$) by the end of the intervention (Week 30). Post-intervention, cooperation levels remained relatively stable, indicating a sustained positive effect of moderate counseling.

In the excessive counseling group, cooperation initially increased during Weeks 10—20 but subsequently declined rapidly due to frequent emotional fluctuations. By the end of the intervention, the cooperation level ($f_c \approx 0.51$) dropped below the pre-intervention level, suggesting a negative disruptive effect of excessive counseling.

In contrast, the control group maintained a relatively stable cooperation level ($f_c \approx 0.52$) throughout the 50-week observation period, with minimal fluctuations.

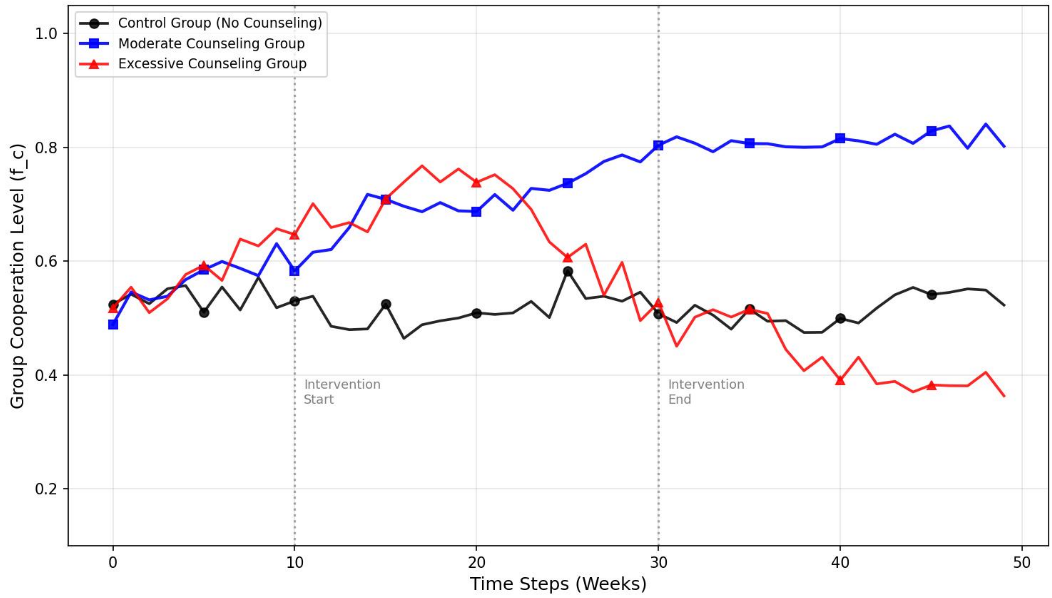

Figure 7. Longitudinal dynamics of group cooperation levels under different counseling conditions (50-week observation period).

5.2. Empirical Study Results

5.2.1. Correlation Analysis

Pearson correlation analysis indicated that the frequency of psychological counseling was significantly positively correlated with the Acceptance Index $(r = 0.412, p < 0.001)$ and the Emotional Value Index $(r = 0.387, p < 0.001)$. The relationship with the Rejection Index exhibited an inverted U-shape, with a significant negative linear correlation $(r = -0.183, p < 0.05)$ and a significant quadratic effect $(r = -0.264, p < 0.01)$.

Furthermore, the Acceptance Index was significantly positively correlated with the composite group cooperation score $(r = 0.523, p < 0.001)$, whereas the Rejection Index was significantly negatively correlated with the composite group cooperation score $(r = -0.318, p < 0.001)$.

5.2.2. Mediation Effect Analysis

Figure 8 presents the path coefficients of the dual-path mediation model. The structural equation model exhibited good fit indices: $\chi^2/df = 2.13, CFI = 0.963, TLI = 0.951, RMSEA = 0.048 (90\% CI: 0.031\text{–}0.065)$, and $SRMR = 0.052$.

The path coefficient from psychological counseling frequency to positive emotional migration (Acceptance Index) was significant $(a_1 = 0.463, p < 0.001)$, and the path from positive emotional migration to group cooperation level was also significant $(b_1 = 0.351, p < 0.001)$. The positive mediation effect $(a_1 \times b_1 = 0.163)$ had a Bootstrap 95% confidence interval of [0.097, 0.241], which does not include zero, indicating a significant mediating effect. Hypothesis H2 was thus supported.

For negative emotional migration (Rejection Index), the path coefficient from counseling frequency was significant under the quadratic term ($a_2 =- 0.287, p < 0.001$; quadratic term coefficient = 0.124, $p < 0.01$), and the path from negative emotional migration to group cooperation level was significant $(b_2 =- 0.219, p < 0.001)$. The negative mediation effect $(a_2 \times b_2 = 0.063)$ had a Bootstrap 95% confidence interval of [0.021, 0.118], supporting hypothesis H3.

The direct effect of psychological counseling frequency on group cooperation $(c' = 0.182, p < 0.05)$ remained significant after controlling for both mediation paths, indicating that emotional migration partially mediates the relationship between psychological counseling and group cooperation.

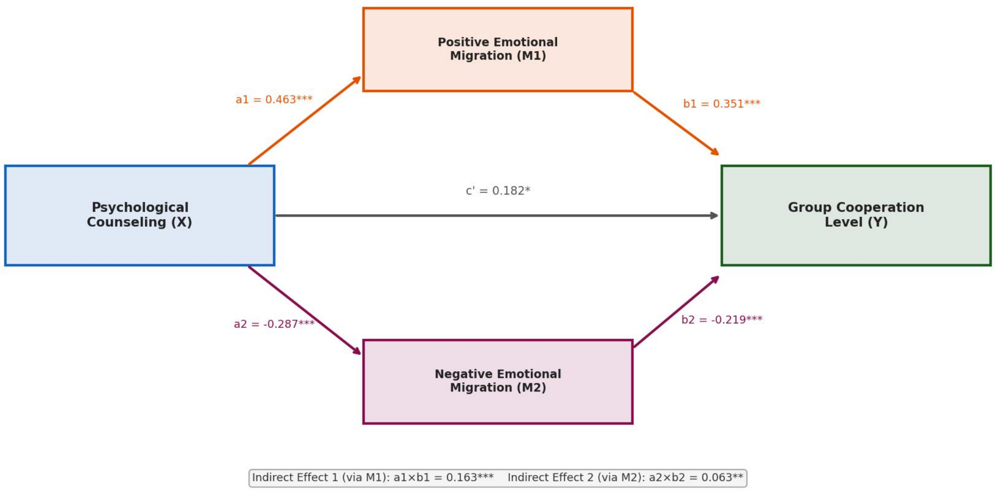

Figure 8. Path coefficients of the dual–path mediation model (Bootstrap 95% CI, n = 1000).

5.2.3. Multidimensional Analysis of Group Cooperation

Figure 9 presents the comparison of scores across different dimensions of group cooperation under varying counseling frequency conditions. The results indicate that the moderate counseling group (2—3 sessions per month) scored significantly higher than both the control group (no counseling) and the excessive counseling group (>6 sessions per month) across all five dimensions: task participation (78.4%), trust level (82.1%), communication quality (79.8%), resource sharing (data not shown), and collective efficacy (80.3%) (one–way ANOVA, $F = 12.47, p < 0.001$; Bonferroni–adjusted post hoc comparisons revealed significant differences between all groups, $p < 0.05$). Notably, the excessive counseling group scored lower on the trust dimension (58.3%) than the low–frequency counseling group (58.9%), indicating that excessive counseling had the most pronounced detrimental effect on trust relationships.

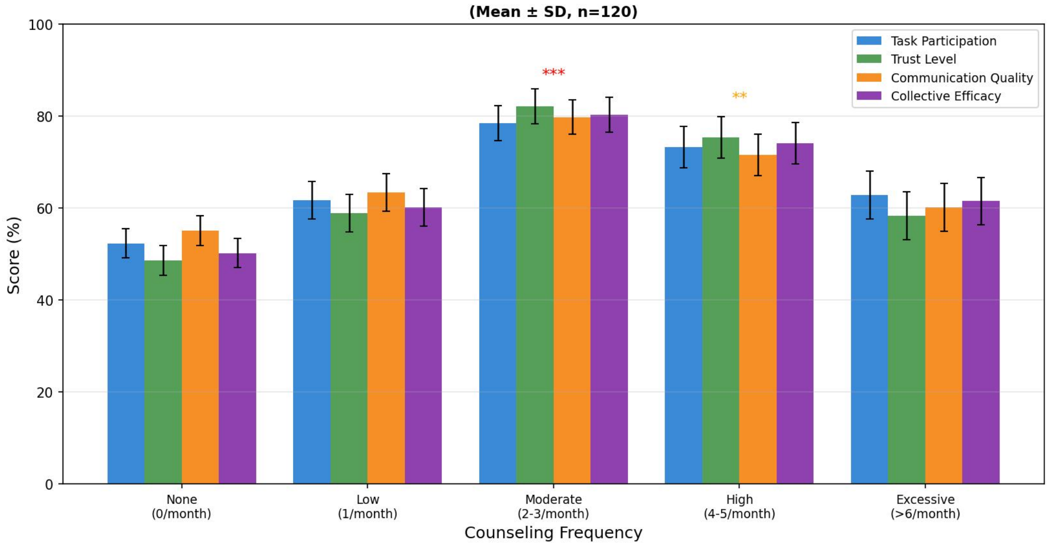

Figure 9. Comparison of group cooperation scores across different dimensions under varying counseling frequencies (mean ± SD, n = 120).

Figure 10 displays a radar chart that visually represents the multidimensional patterns of cooperation behavior across the three experimental groups. The chart further confirms the overall advantage of the moderate counseling group in all dimensions of group cooperation.

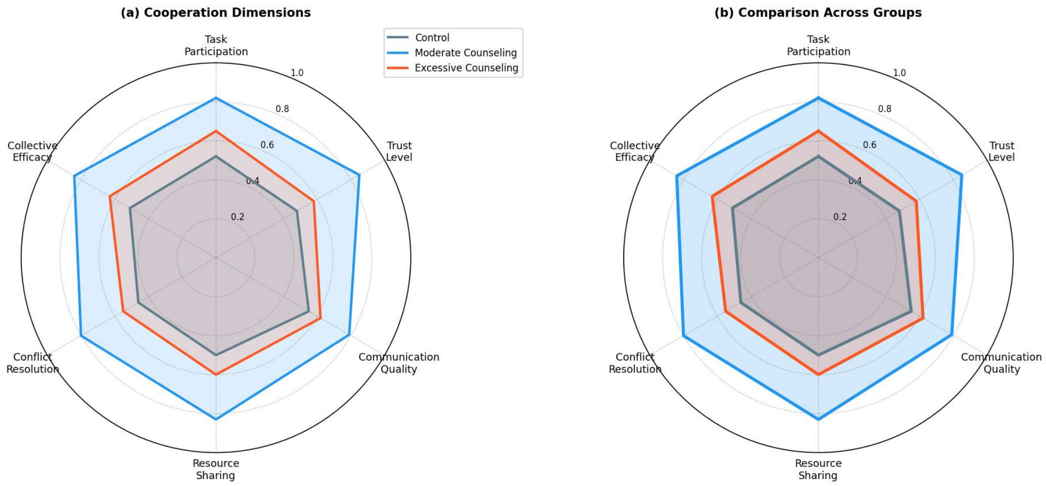

Figure 10. Radar chart of multidimensional assessment of group cooperation under different counseling conditions.

5.2.4. Scatter Analysis of Emotional Migration Indices and Group Cooperation Levels

Figure 11 presents the scatter plots of positive emotional migration (Acceptance Index) and negative emotional migration (Rejection Index) in relation to group cooperation levels. Positive emotional migration was significantly positively correlated with group cooperation *($r = 0.523, p < 0.001$)*, whereas negative emotional migration was significantly negatively correlated with group cooperation *($r = -0.318, p < 0.001$)*.

When stratified by grade, the scatter distribution shows that the positive emotional migration effect was more stable among third- and fourth-year students, indicated by higher clustering of data points. In contrast, first-year students exhibited the greatest dispersion, suggesting that the impact of emotional migration on cooperative behavior varies significantly across grade levels.

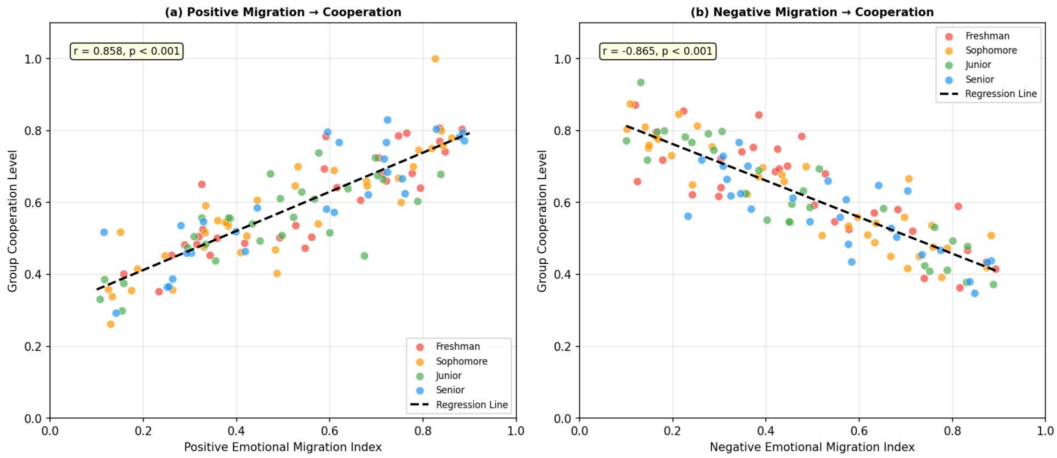

Figure 11. Scatter plots of emotional migration indices and group cooperation levels (n = 120).

5.2.5. Distribution Characteristics of Cooperation Scores

Figure 12 presents violin plots depicting the distribution of group cooperation scores under five different counseling frequency conditions. The moderate counseling group (2—3 sessions per month) exhibited the most concentrated distribution (SD = 8.0), with the highest median score (approximately 79 points), and a distribution shape approximating normality. This indicates that moderate counseling produced a stable and consistent cooperative enhancement effect.

In contrast, the excessive counseling group (>6 sessions per month) showed the most dispersed distribution (SD = 16.0) with a bimodal pattern, suggesting a highly heterogeneous impact of excessive counseling. Some students maintained relatively high levels of cooperation under excessive counseling, whereas others experienced a significant decline in cooperative behavior.

Sensitivity analyses indicated that, after excluding two extreme outliers, the primary conclusions remained robust. The bootstrap 95% confidence intervals for the mediation effects did not include zero, and both the direction and significance of effects remained unchanged.

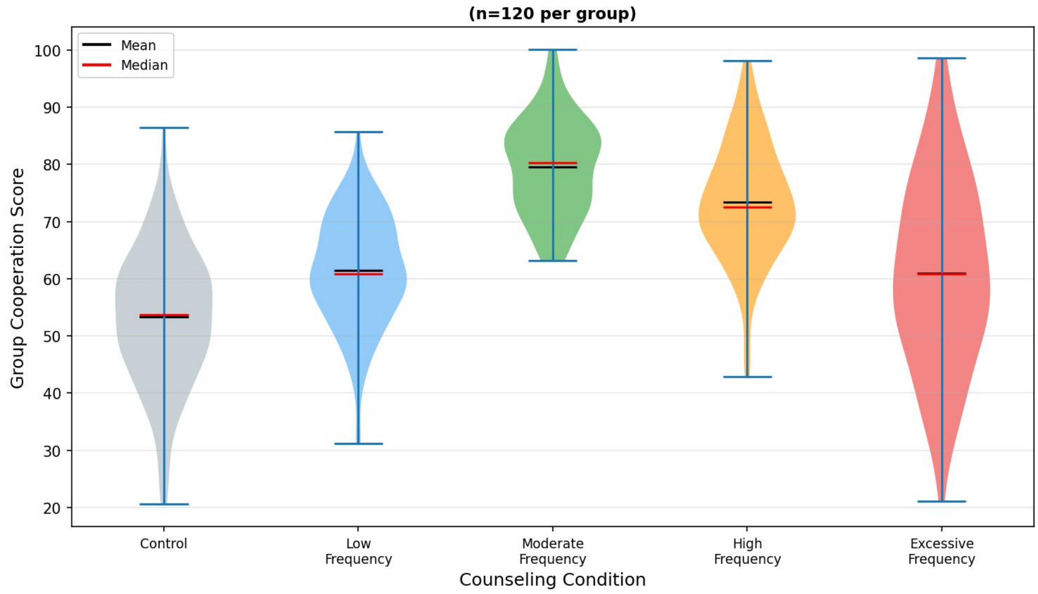

Figure 12. Violin plots of group cooperation score distributions under different counseling frequency conditions (n = 120 per group).

6. Discussion

6.1. Mechanistic Interpretation of the "Double-Edged Sword" Effect of Emotional Migration

The core finding of this study—the "double-edged sword" effect of emotional migration on group cooperation—is highly consistent with the results reported by Ji et al. (2025) in abstract public goods game models [9]. However, this study further elucidates the specific mechanisms underlying this effect within the context of university students' educational settings.

From a game-theoretic perspective, the cooperative-promoting mechanism of moderate emotional migration can be understood as follows: when the migration intensity falls within an optimal range, cooperators can effectively "follow" other cooperators and "avoid" defectors, thereby forming stable cooperative clusters within the social network. This clustering effect increases interaction frequency among cooperators and reduces the success probability of free-riding, promoting the evolutionary stability of cooperative strategies at the game-theoretic equilibrium level [28]. In a university classroom context, this corresponds to students with positive psychological states forming stable study groups with other proactive peers, jointly participating in class-related collective tasks, and establishing virtuous cycles of cooperation.

However, when migration intensity exceeds a critical threshold, the cooperative-promoting effect reverses into a cooperative-disrupting effect. From the perspective of complex network dynamics, excessively high migration intensity leads to frequent restructuring of network topology, preventing the formation of stable cooperative clusters and hindering the establishment of trust relationships among cooperators [29]. In classroom settings, this corresponds to excessive psychological counseling causing frequent emotional fluctuations, unstable social choices, and rapid changes in interaction partners, resulting in persistent instability in the class cooperation network and undermining the accumulation of trust.

This mechanism aligns with the "optimal window for emotion regulation" theory in educational psychology. Gross's (1998) process model of emotion regulation indicates that excessive emotion regulation interventions may deplete individuals' emotional resources, thereby reducing social adaptability [23]. The empirical results of this study provide supporting evidence for the applicability of this theory at the group cooperation level.

6.2. Theoretical Implications of the Optimal Intervention Range

The optimal intervention parameter ranges identified in this study ($v \in [0.10, 0.30]$, $R \in [0.30, 0.50]$, counseling frequency of 2—3 sessions/month) carry significant theoretical implications. These findings suggest that the influence of emotional migration on group cooperation is not monotonically linear but exhibits a "sweet spot" where the positive effects of emotional migration (promoting cooperator aggregation) outweigh the negative effects (disrupting network stability), resulting in a net positive effect.

Compared with Barsade's (2002) work on group emotional contagion [26], this study innovatively introduces a spatial dynamics dimension, revealing the "distance effect" in emotional transmission: overly small interaction radii limit the spread of emotional signals, reducing cooperative-promoting effects, whereas excessively large interaction radii dilute emotional signals, making it difficult for individuals to form clear emotional assessments, which may lead to irrational social choices. This finding aligns with Johnson and Johnson's (2009) discussion on the need for appropriate boundaries in positive interdependence in cooperative learning [25], providing a theoretical basis for designing the scale of cooperative learning groups.

6.3. Grade-Level Differences and Individual Heterogeneity

The scatterplot analysis in Figure 10 highlights significant grade-level differences in the effect of emotional migration: the impact on cooperative behavior is more stable among third- and fourth-year students, while first-year students exhibit the greatest individual variability. This can be explained from two perspectives: first, higher-grade students have experienced longer periods of social adjustment within their class, resulting in a more stable emotional evaluation system and more regular patterns of emotional migration; second, first-year students are in the university adaptation phase, with greater emotional volatility, making their emotional migration behavior more susceptible to external environmental influences, thus exhibiting higher individual heterogeneity.

The bimodal distribution observed in the violin plot of the excessive counseling group (Figure 12) further supports the importance of individual heterogeneity. This suggests that excessive psychological counseling produces highly differentiated effects across individuals, likely due to interactions among individual differences in emotion regulation capacity, personality traits, and pre-existing social network structures. These observations are consistent with Gross's (1998) assertion that the effectiveness of emotion regulation strategies varies significantly across individuals [23].

6.4. Limitations

Several limitations of this study should be noted. First, the sample was drawn from a single university, which may limit the generalizability of the findings. Future research should expand the sample to include students from different types of universities (e.g., comprehensive universities, STEM-focused institutions, liberal arts colleges) to enhance representativeness. Second, the cross-sectional design restricts the strength of causal inferences; longitudinal studies would be more suitable for capturing the dynamic evolution of emotional migration mechanisms. Third, the simulation model necessarily simplifies real-world conditions. Complex factors present in actual classroom social networks—such as hierarchical structures and small-group effects—were not incorporated into the model. Fourth, the use of self-reported questionnaire data carries the potential risk of response bias. Future research could supplement self-reports with objective behavioral indicators, such as social network analysis of online interactions (e.g., WeChat group data), to provide a more comprehensive understanding of emotional migration and cooperative behavior.

7. Conclusion

7.1. Key Findings

By integrating public goods game theory, complex network dynamics, and educational psychology, this study systematically elucidates the mediating role of emotional migration in the relationship between psychological counseling and group cooperation among university students. Four core patterns emerge:

- Pattern 1: Dual-pathway mediation of emotional migration. Psychological counseling influences group cooperation through two distinct emotional migration pathways: positive emotional migration (enhanced acceptance) and negative emotional migration (changes in rejection). The mediating effect of the positive pathway ($a_1 \times b_1 = 0.163$) is substantially greater than that of the negative pathway ($a_2 \times b_2 = 0.063$), indicating that psychological counseling primarily promotes group cooperation by enhancing students' emotional acceptance;

- Pattern 2: The "double-edged sword" effect of emotional migration. The impact of emotional migration on group cooperation exhibits a pronounced inverted U-shaped nonlinearity. Moderate emotional migration ($v \in [0.10, 0.30]$) facilitates the clustering of cooperators, forming stable cooperative groups and significantly increasing group cooperation ($f\_c \approx 0.82$—0.95). In contrast, excessive emotional migration ($v > 0.35$) disrupts network topology stability, leading to the collapse of the cooperative system (f_c approaches zero);
- Pattern 3: Moderating effect of interaction radius. The interaction radius (R) significantly moderates the relationship between emotional migration and cooperation, with an optimal range of $R \in [0.30, 0.50]$. A larger interaction radius lowers the critical threshold for optimal migration strength, rendering the cooperative system more sensitive to emotional fluctuations. This finding corresponds to the practical observation that managing cooperation becomes more challenging in larger classroom settings;
- Pattern 4: Principle of moderate psychological counseling. Empirical data indicate an inverted U-shaped relationship between counseling frequency and group cooperation. Optimal cooperation is achieved under moderate counseling frequency (2—3 sessions per month), whereas excessive counseling (>6 sessions per month) reduces cooperation levels. This provides practical guidance for the scheduling and frequency design of university counseling programs.

7.2. Implications

Theoretical contributions: This study is the first to translate the emotional migration mechanism from abstract game-theoretic models into the context of higher education. By constructing an integrative analytical framework spanning game theory, complex networks, and educational psychology, it enriches the theoretical understanding of emotional migration in educational settings and offers new avenues for applying public goods game theory to educational management.

Practical guidance: For university psychological counseling, the findings highlight the importance of adhering to a "moderate intervention" principle to avoid emotional overload. Emphasis should be placed on group and peer counseling to leverage network effects, and optimizing classroom social network structures (maintaining an appropriate interaction radius) can maximize the cooperative benefits of counseling. Special attention should be given to first-year students' heterogeneity, with tailored psychological support strategies provided accordingly.

7.3. Future Research Directions

Future studies could further explore three directions: First, conduct longitudinal, cross-institutional, and cross-cultural research to examine the generalizability of emotional migration mechanisms and potential cultural variations. Second, integrate social network analysis (e.g., mining interactions from WeChat groups) to build more precise dynamic models of classroom social networks, enhancing ecological validity. Third, investigate the impact of AI-assisted psychological counseling systems on emotional migration, providing theoretical support for the development of intelligent mental health services in universities.

References

[1] Johnson D W, Johnson R T. An educational psychology success story: Social interdependence theory and cooperative learning[J]. Educational Researcher, 2009, 38(5): 365-379.

[2] Wentzel K R, Muenks K. Peer influence on students' motivation, academic achievement, and social behavior[J]. Advances in Motivation and Achievement, 2016, 19: 13-48.

[3] Wang X, Zhang H, Liu Y, et al. Prevalence and associated factors of mental health problems among Chinese college students: A systematic review and meta-analysis[J]. Frontiers in Psychiatry, 2020, 11: 582305.

[4] Frazier P, Gabriel A, Merians A, et al. Understanding stress as an impediment to academic performance[J]. Journal of American College Health, 2019, 67(6): 562-570.

[5] Hatfield E, Cacioppo J T, Rapson R L. Emotional contagion[J]. Current Directions in Psychological Science, 1993, 2(3): 96-100.

[6] Ji Y, Tan M, Long H. Effect of emotional migration on cooperation for public goods games on continuous two-dimensional space[J]. Scientific Reports, 2025, 15: 32922.

[7] Fredrickson B L. The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions[J]. American Psychologist, 2001, 56(3): 218-226.

[8] Hardin G. The tragedy of the commons[J]. Science, 1968, 162(3859): 1243-1248.

[9] Ji Y, Tan M, Long H. Effect of emotional migration on cooperation for public goods games on continuous two-dimensional space[J]. Scientific Reports, 2025, 15: 32922.

[10] Nowak M A, May R M. Evolutionary games and spatial chaos[J]. Nature, 1992, 359(6398): 826-829.

[11] Santos F C, Pacheco J M. Scale-free networks provide a unifying framework for the emergence of cooperation[J]. Physical Review Letters, 2005, 95(9): 098104.

[12] Perc M, Jordan J J, Rand D G, et al. Statistical physics of human cooperation[J]. Physics Reports, 2017, 687: 1-51.

[13] Szolnoki A, Perc M. Coevolutionary success-driven multigames[J]. EPL (Europhysics Letters), 2012, 100(2): 28005.

[14] Li X, Jusup M, Wang Z, et al. Punishment diminishes the benefits of network reciprocity in social dilemma experiments[J]. Proceedings of the National Academy of Sciences, 2018, 115(1): 30-35.

[15] Zhang H, Perc M, Wang Z. Evolution of cooperation on interdependent networks with the prisoner's dilemma and snowdrift game[J]. Scientific Reports, 2022, 12: 9005.

[16] Wang Z, Kokubo S, Jusup M, et al. Universal scaling for the dilemma strength in evolutionary games[J]. Physics of Life Reviews, 2015, 14: 1-30.

[17] Chen X, Szolnoki A, Perc M. Probabilistic sharing solves the problem of costly punishment[J]. New Journal of Physics, 2014, 16(8): 083016.

[18] Long H, Tan M, Ji Y. Heterogeneous investments induced by emotion improve cooperation in public goods games[J]. Applied Mathematics and Computation, 2023, 452: 128049.

[19] Watts D J, Strogatz S H. Collective dynamics of 'small-world' networks[J]. Nature, 1998, 393(6684): 440–442.

[20] Barabási A L, Albert R. Emergence of scaling in random networks[J]. Science, 1999, 286(5439): 509–512.

[21] Xiao Y, Chen D, Wei S, et al. Cooperation in the mobile public goods game[J]. Physica A: Statistical Mechanics and its Applications, 2021, 567: 125697.

[22] Chen X, Fu F, Wang L. Interaction stochasticity supports cooperation in spatial prisoner's dilemma[J]. Physical Review E, 2008, 78(5): 051120.

[23] Gross J J. The emerging field of emotion regulation: An integrative review[J]. Review of General Psychology, 1998, 2(3): 271–299.

[24] Garnefski N, Kraaij V, Spinhoven P. Negative life events, cognitive emotion regulation and emotional problems[J]. Personality and Individual Differences, 2001, 30(8): 1311–1327.

[25] Johnson D W, Johnson R T. An educational psychology success story: Social interdependence theory and cooperative learning[J]. Educational Researcher, 2009, 38(5): 365–379.

[26] Barsade S G. The ripple effect: Emotional contagion and its influence on group behavior[J]. Administrative Science Quarterly, 2002, 47(4): 644–675.

[27] Topping K J. Trends in peer learning[J]. Educational Psychology, 2005, 25(6): 631–645.

[28] Axelrod R, Hamilton W D. The evolution of cooperation[J]. Science, 1981, 211(4489): 1390–1396.

[29] Rand D G, Nowak M A. Human cooperation[J]. Trends in Cognitive Sciences, 2013, 17(8): 413–425.