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A Study on Strategies for Optimizing Emotional Communication in Peer Counseling on Social Networks Based on AI Algorithms

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SUMMARY: *Currently, student mental health issues are becoming increasingly prominent and have become a major challenge that families, society, and schools must address urgently. Peer mental health counseling conducted on social media platforms offers distinct advantages. This study explores emotional communication strategies in peer mental health counseling and proposes a self-regulation scheme based on peer counseling. This scheme is implemented using the Kernighan-Liu community mining algorithm and a social network analysis-based information recommendation algorithm. Based on this framework, a comparative experiment was conducted with students from a selected school to investigate the effectiveness of the peer counseling self-regulation method. The information recommendation algorithm proposed in this paper demonstrates high detection effectiveness and efficiency, with a detection rate of 92.61% and a runtime of 0–11.71 seconds. After experiencing the methods proposed in this paper, students' peer counseling competition scores, peer counseling satisfaction, and willingness to seek help significantly improved at the 1% level, increasing by 39.62%, 111.18%, and 73.14%, respectively. The number of school crises, students' SCL-90 data, and peer counseling occupational burnout levels decreased by 45%, 7.53%, and 20.52%, respectively, validating the promotional effect of peer counseling self-regulation methods on the emotional transmission of peer counseling.*

KEYWORDS: *community mining; information recommendation; social network analysis; peer counseling*

1 Introduction

Mental disorders have become one of the major threats to human health in the 21st century [1]. Research reports indicate that nearly 1 billion people worldwide suffer from varying degrees of mental health issues, with over 350 million people suffering from depression and approximately 264 million from anxiety disorders [2, 3]. The growing number of individuals with mental disorders has become one of the key factors affecting social harmony. When individuals experience mental health issues, their first choice is to confide in friends, followed by mothers, classmates, partners, fathers, and peers of the same age. Professional psychological counseling is the last resort, with less than 35% opting for counseling [4-6]. In terms of the influence on adolescents' moral development, peer groups have surpassed family and school to become the

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second most significant factor, with mass media ranking first [7, 8]. It can be seen that when people encounter psychological issues, they are more willing to seek help from peers. This phenomenon is particularly pronounced among students, especially college students [9].

Peer psychological counseling refers to the process by which individuals of similar biological and psychological ages, who have undergone psychological training, provide psychological assistance to peers in need under the supervision of professional counseling teachers. The counseling methods primarily involve listening and offering support [10]. It differs from professional counseling in that it allows counselors to provide their own suggestions for peers to consider [11]. Peer psychological counseling has inherent advantages, such as spending more time together, being on equal footing, and communicating without pressure; sharing a common language and avoiding generational gaps; having shared emotional experiences and easily resonating with one another; and when peers encounter confusion, they can provide timely psychological support and assistance due to their similar ages and experiences [12-15]. Peer counseling has a coverage rate exceeding 68%, but its effectiveness rate has not exceeded 45% [16]. Literature [17] explores the public's interest in self-help and peer support projects disseminated online, with over 60% of respondents willing to try such projects. Most people prefer close friends or partners as counselors, and they are more interested in projects that are completely independent of websites. Literature [18] used open Facebook groups as data to explore the effectiveness of online peer mutual support in mental health counseling. Online peer mutual support enhanced users' sense of belonging and self-efficacy, reduced feelings of loneliness, and had a positive impact on mental health.

With the development of social networks, an increasing number of people tend to share their lives and feelings on these platforms. The daily page views related to psychological topics can exceed 200 million. Many users record and discuss psychological issues on the platform, while others provide psychological education or act as counselors [19, 20]. Emotional motivation is the primary motivation for users to use social networks, expanding the scope of peer mental health counseling services and providing convenience for mental health counselors to understand users' psychological dynamics and convey developmental counseling concepts [21-23]. Emotion is also a crucial factor in identifying users' psychological issues on social networks, making research on emotional computation and dissemination in the context of mental health counseling on social networks of utmost importance.

Artificial intelligence (AI) algorithms assist in emotional computation and propagation within social networks, making AI peer psychological counseling feasible. Literature [24] utilizes natural language processing technology and a constructed hybrid deep learning neural network model to detect depression in text content posted on social networks. Literature [25] established an AI framework for self-organizing emotional modeling and analysis, which integrates data from social media to build models and performs emotional classification and analysis of conversations in online mental health support forums. Literature [26] mentioned that emotional analysis and emotional computing, as natural language processing technologies, are effective tools in monitoring and detecting mental illnesses, thereby developing an integrated multimodal system for depression monitoring. Literature [27] explores the effectiveness of AI in detecting emotions in social media text data and analyzes the effectiveness of AI-based social media emotion detection systems, with significant results indicating a promising future for AI in this field. Literature [28] shows that AI can detect early mental health trends among users across different social media platforms, languages, cultural backgrounds, and types of mental health issues, thereby aiding mental health interventions. Literature [29] introduces an online social therapy application for providing online psychological rehabilitation counseling, which is implemented through computing and AI and optimized using natural language analysis and chatbot technology. Literature [30] summarizes that AI can not only be used to identify depressed patients on social media but also to optimize depression treatment plans, such as drug dosage and drug combinations, providing personalized psychological treatment plans. Literature [31] points out that online peer psychological counseling based on AI tools with dialogue interaction has been developed, but it needs to be optimized in terms of implementation decisions, productivity, management, and training.

After discussing the advantages of peer psychological counseling in social networks, the study proposes a peer psychological counseling self-regulation plan, which is based on personalized information recommendations for communities mined from user data. The Kernighan-Liu algorithm was used for community mining. Based on social network analysis centrality metrics, a comprehensive centrality was constructed to identify core community users. Then, from two dimensions—friend recommendations and resource recommendations—a recommendation method based on core community users was designed. Using learning resources as the test object, comparative experiments were conducted with other recommendation algorithms. By comparing the anomaly detection rate and algorithm runtime, the performance of the proposed information recommendation method was analyzed. Finally, a comparative experiment was conducted using students from a certain school as a sample. Through statistical analysis of two groups of students—those who had experienced peer psychological counseling self-regulation methods and those who had not—in terms of peer psychological counseling competitions, the number of school crises, student SCL-90 data, peer counseling occupational burnout levels, peer counseling satisfaction, and willingness to seek help, the practical effectiveness of the designed peer psychological counseling self-regulation method was verified.

2 Advantages of peer counseling on social networks

Peer group counseling is a process of helping individuals recognize, explore, and accept themselves through interpersonal interactions within a group, under the guidance of a leader. It utilizes group dynamics theory and appropriate counseling techniques to facilitate individuals in improving their relationships with others, learning new attitudes and behaviors, enhancing their adaptability, and preventing or resolving problems while stimulating their potential. Peers are more likely to communicate and accept one another, as the natural barriers between them are smaller, their defensiveness is lower, they share more commonalities, and their interactions are more frequent, giving them inherent advantages.

2.1 Supplementing the shortage of psychological counselors

At present, university mental health counseling services and staff are severely understaffed. Relying solely on mental health professionals to conduct mental health education efforts is merely a temporary fix. Mobilizing college students' initiative and enthusiasm, guiding them to serve as peer group counselors, and conducting group counseling under the guidance and supervision of mental health professionals is a scientifically sound approach, a counseling technique, and the very essence of peer counseling. Peer group counseling is more efficient and has a broader reach than individual peer counseling, which is why it has gained widespread popularity among universities. It helps an increasing number of college students resolve their mental health issues, enabling them to better adapt to society in the future. Additionally, it has become an important means of identifying, developing, and leveraging the leadership and organizational potential of college students.

2.2 Breaking down psychological barriers

Group identity is a prominent characteristic of college student groups. Group counseling, which uses the group as its primary focus, can mitigate individual resistance. Group counseling leverages the natural tendency of young people to form groups, using subtle methods to guide and influence college students to make changes on their own. While college students' distinct individual personalities may make them resistant to authority, they are also more susceptible to suggestion and group influence. The natural trust among peers is a significant advantage for mutual support. The learning and living rhythms of classmates are relatively consistent, with ample time and harmonious space for communication and interaction. College students are more inclined to confide their troubles and share their feelings with peers. Therefore, peer group counseling can help guide college students to seek assistance from friends or classmates who understand them better when faced with difficulties or confusion, rather than hesitating whether to seek help from professional counselors. This approach helps break down psychological barriers to seeking help and facilitates the effective resolution of practical issues.

3 Peer psychological counseling self-regulation method optimized based on AI algorithms

This paper addresses the need for peer psychological counseling and emotional support in social networks by proposing an AI algorithm-optimized peer psychological self-regulation method. It utilizes the analysis, organization, and maintenance of professional psychological knowledge, combined with data mining and information service technologies, to help users learn and understand relevant psychological knowledge, create peer relationship networks, and thereby achieve a “self-help—helping others—mutual assistance” mechanism for peer psychological counseling. The peer psychological self-regulation solution, as shown in Figure 1, is primarily divided into three components: a human-machine interface, a database, and an expert recommendation model.

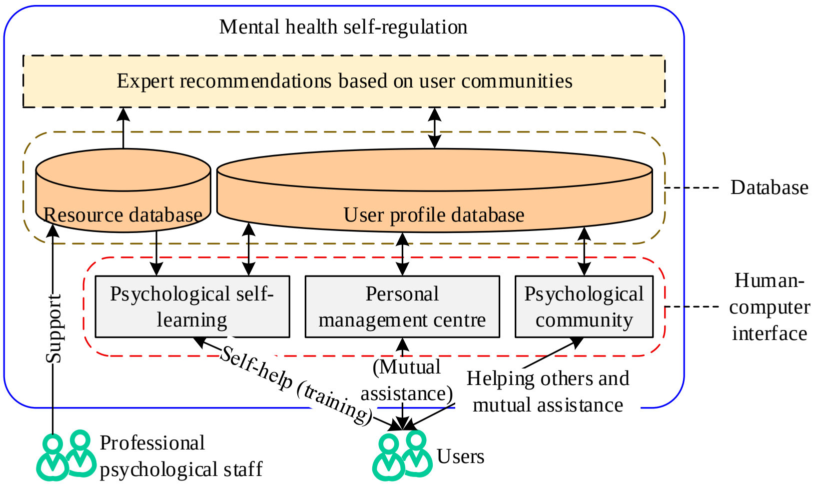


Figure 1: Peer psychological self-help adjustment solution

3.1 Community mining algorithm based on KL

Society refers to the collection of individuals and the relationships between them. In a broad sense, a community is a subset of society, where the members of this subset share certain similar characteristics or satisfy specific relationships among themselves.

Society $Society(V, E)$ denotes the set of individuals V and the set of relationships between individuals E. A community is defined as a subset of society, where the members of this subset share certain similar characteristics or satisfy specific relationships among themselves. A community can be represented as a triple $Community = \langle G, F, T \rangle$, where $G \subseteq V$, $F \subseteq E$, and T denotes the attributes of members or the relationships between members.

The Kernighan-Liu algorithm, abbreviated as the KL algorithm, decomposes a network into two communities through a heuristic process based on greedy optimization. The algorithm introduces an optimization function Q, defined as the difference between the number of edges within the two communities and the number of edges between the two communities. The algorithm's execution process:

(1) Manually set the size of the communities and the initial configuration of the two communities.

(2) Examine all pairs of nodes taken from the two communities, calculate the change in the optimization function ΔQ, select the pair of nodes that maximizes ΔQ, and then swap the two nodes. Nodes that have been swapped are no longer swapped in subsequent processes. Repeat until all nodes in one group have been swapped.

(3) Examine all swaps from step (2) and identify the one that maximizes the change in ΔQ. The distribution of nodes in the two communities at this point represents the optimal partition of the network.

3.2 Information recommendation based on core users in the community

This section mainly studies how to use the user community data that has been mined to recommend relevant information to users. First, we analyze and study the centrality indicators in social network analysis, define comprehensive centrality, and propose a community core mining algorithm based on comprehensive centrality. This algorithm can analyze the centrality of the user community that has been mined and rank it according to the comprehensive centrality value, thereby recommending friends and personalized information to users.

3.2.1 Centrality Measures in Social Network Analysis

Centrality is a quantitative analysis indicator of “power” in social network analysis. Power characterizes an individual's status and influence in a social network. In order to formally define and quantitatively analyze power, the concept of “centrality” has been introduced into social network analysis methods. Centrality is used to measure the centrality of a single node.

(1) Degree centrality

“Degree centrality” is the simplest and most intuitive metric. It describes the degree to which a node is located at the “core” of a graph and characterizes the ability of that node to develop relationships with other nodes in the graph. Degree centrality is divided into absolute degree centrality and relative degree centrality. The absolute degree centrality of node n_i (denoted by C_{ADI}) is the degree of that node, i.e.:

$$C_{ADI} = d(n_i) \tag{1}$$

The relative degree centrality of point n_i (denoted by C_{RDI}) is defined as the ratio of the degree of the point to its maximum possible degree, i.e.:

$$C_{RDI} = \frac{d(n_i)}{n-1} \tag{2}$$

where n is the number of nodes in the graph.

(2) Intermediate centrality

"Intermediate centrality" describes the extent to which a node acts as an 'intermediary' (or "bridge"), characterizing the node's ability to control the interactions between other nodes in the graph.

Intermediate centrality is divided into absolute intermediate centrality and relative intermediate centrality. Suppose the number of geodesics between nodes n_j and n_k in the graph is denoted by g_{jk}, the ability of the third node n_i to control the interactions between these two nodes is denoted by $b_{jk}(i)$, defined as the probability that the node lies on the geodesic line between nodes n_j and n_k. The number of geodesic lines between nodes n_j and n_k that pass through node n_i is denoted by $g_{jk}(i)$, then:

$$b_{jk}(i) = \frac{g_{jk}(i)}{g_{jk}} \tag{3}$$

The absolute intermediate centrality of vertex n_i (denoted as C_{ABi}) is defined as the sum of the control power of this vertex over all pairs of vertices in the graph, i.e.:

$$C_{ABi} = \sum_j^n \sum_k^n b_{jk}(i),\ j \neq k \neq i \ And\ j < k \tag{4}$$

The relative intermediate centrality of point n_i (denoted as C_{RBi}) is the normalized form of its absolute intermediate centrality, which is the ratio of the actual absolute intermediate centrality of the point to its maximum possible absolute intermediate centrality, defined as:

$$C_{RBi} = \frac{2C_{ABi}}{n^2 - 3n + 2} = \frac{2\sum_j^n \sum_k^n b_{jk}(i)}{n^2 - 3n + 2} \tag{5}$$

(3) Proximity to the center

"Proximity to the center" describes how close a point is to all other points in the graph. If the distance between this point and all other points in the graph is short, it means that this point is "close" to all other points in the graph, i.e., its proximity to the center is high. Closeness to the center characterizes a point's ability to escape the control of other points in the graph. If an actor in a network relies less on other actors in its interactions with them, then that actor has a high closeness to the center.

Proximity to the center is divided into absolute proximity to the center and relative proximity to the center. The absolute proximity to the center of point n_i (denoted as C_{ACi}) is the sum of the distances between this point and all other points in the graph, that is:

$$C_{ACi} = \sum_{j=1}^n d(i, j) \tag{6}$$

where $d(i, j)$ denotes the distance between points n_i and n_j.

The relative proximity to the center (denoted as C_{RCi}) of point n_i is the normalized form of its absolute proximity to the center, which is the ratio of the actual absolute proximity to the center of the point to its maximum possible absolute proximity to the center. It has been proven that the relative proximity to the center is:

$$C_{RCi} = \frac{C_{ACi}}{(n-1)^2} = \frac{\sum_{j=1}^{n} d(i, j)}{(n-1)^2} \tag{7}$$

3.2.2 Community core mining based on comprehensive centrality

(1) Comprehensive centrality

When quantifying the contribution of the three types of centrality to the final ranking of nodes, the standard score (also known as z-score) of each type of centrality is used as a measure of the position of a node's centrality among all nodes. The mean of the standard scores of the three types of centrality is then calculated to serve as a measure of the node's comprehensive centrality in the community. Based on this, a definition of comprehensive centrality is provided.

Comprehensive centrality measures a node's centrality from three aspects: degree, betweenness, and closeness, thereby yielding a multi-dimensional centrality value for the node. Let $Z_{RP}(i)$, $Z_{RB}(i)$, and $Z_{RC}(i)$ denote the standard scores of the relative degree centrality, relative intermediate centrality, and relative proximity centrality of node i, respectively. Then, the formula for the comprehensive centrality $C(i)$ is:

$$C(i) = (Z_{RP}(i) + Z_{RB}(i) + Z_{RC}(i)) / 3 \tag{8}$$

The general formula for the standard score $Z_{RX}(i)$ of the three types of centrality is:

$$Z_{RX}(i) = \frac{C_{RX}(i) - \overline{C_{RX}}}{\sigma_{RX}} = \frac{C_{RX}(i) - \overline{C_{RX}}}{\sqrt{\dfrac{\sum_{j=1}^{n} (C_{RX}(j) - \overline{C_{RX}})^2}{n}}} \tag{9}$$

Among these, σ_{RX} is the standard deviation of centrality, and $\overline{C_{RX}}$ is the average value of centrality.

(2) Algorithm Flowchart

The algorithm flowchart for community core mining based on comprehensive centrality is shown in Figure 2. This algorithm considers the centrality of nodes from three aspects: the degree of social network nodes, the distance between nodes, and the distance between nodes, and introduces a standard score metric, which is suitable for comparing the centrality of nodes between different communities and networks.

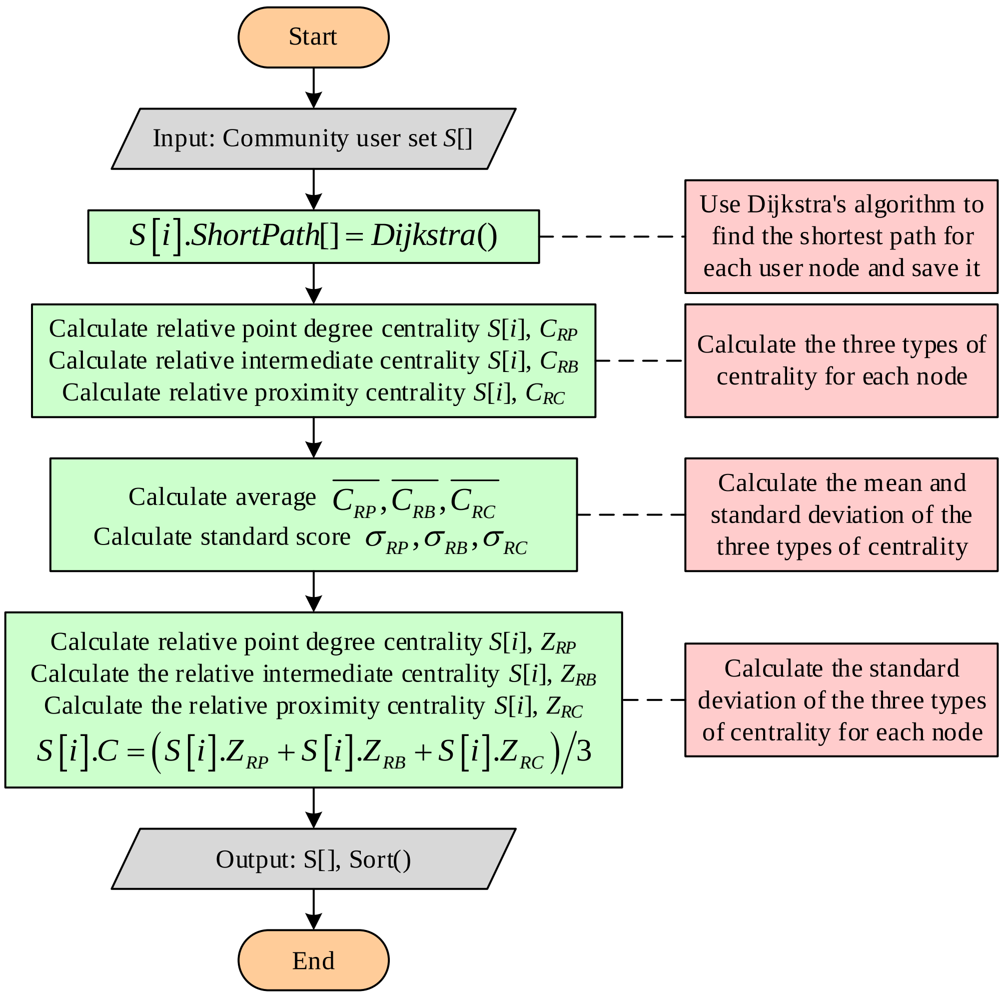


Figure 2: The Community core mining algorithm process based on the integrated center degree

3.2.3 Recommendations based on core users in the community

The community core mining algorithm based on comprehensive centrality can be used to obtain the centrality ranking results of community users. Based on these ranking results, personalized friend recommendations and resource recommendations can be made to users.

(1) Friend recommendations

When making friend recommendations, in addition to the original centrality ranking results, we also incorporate a measure of the similarity of personalized features between the specified user and other users in the community core. This provides users with a more precise ranking of community core users. To this end, we define the personalized feature similarity $C-P$ similarity (denoted as $CPS(i)$) of community users based on the comprehensive centrality ranking.

$C-P$ similarity adds the similarity of personalized features between users to the comprehensive centrality of nodes, thereby enabling the precise identification of users of interest to the target user. Let $C(j)$ denote the comprehensive centrality of node j, $P(i,j)$ is the similarity of personalized features between nodes i and j, and α is the threshold for centrality and similarity of personalized features, where $0 \le \alpha \le 1$. Then, the formula for calculating the $C-P$ similarity $CPS(i)$ of node i is:

$$CPS(i) = \alpha C(i) + (1-\alpha)P(i, j) \tag{10}$$

By calculating the similarity between target users and core users in the community using the $C-P$ method and sorting the results, we can identify other users in the community who are of interest to the target users or who are similar to them. By excluding users who are already friends with the target users, we obtain a list of users who can be recommended as friends.

(2) Resource Recommendation

In different application contexts, two scenarios may arise: one where there are only records of users' usage or interest in resources, with no related evaluation records, and another where the system collects users' evaluations of resources they have used or are interested in, including textual comments on the resources and satisfaction ratings. This section provides a brief overview of how to utilize the similarity data between target users and community core users, which has been mined, for resource recommendation in these two scenarios.

1) Top-N Resource Recommendation

The main approach involves analyzing the attributes of resources or the relationships between resources of the target user's adjacent users or similar users, thereby recommending the most suitable resource information to the target user.

Frequent Item Recommendation: Frequent item recommendation is a relatively simple recommendation method that can provide users with resource information similar to their experience to some extent. However, since it does not analyze the personalized characteristics of users or resources, the recommendation results are not very precise or effective.

Based on the application of the similarity between community users $C-P$ discussed earlier in this article, the main idea of this algorithm is to scan the resource records of each core user in the community, select the top resources with the highest frequency that are not present in the target user's records, and use these as the recommendation results.

Association rule recommendation: In data mining technology, association rule patterns are an important type of knowledge pattern. They belong to descriptive patterns and are mainly used to mine the intrinsic relationships between transactions in large transaction systems or large data warehouses.

Item Set: A set composed of items, where a set containing k items is referred to as a k-item set.

Frequent Item Set: If an item set appears in a transaction database with a frequency greater than the minimum support threshold, it is referred to as a frequent item set. Since frequent item sets reflect strong associations between transactions, the primary process of association rules is to identify frequent item sets.

Support: Represents the probability of events occurring simultaneously, and indicates whether the rule is applicable to most people based on the probability. Define events X and Y, where $X => Y$ means that if event X occurs, event Y also occurs simultaneously.

The definition of support is:

$$\sup per\left(X => Y\right) = \sup per\left(X \cup Y\right) = P\left(X \cup Y\right) \tag{11}$$

Confidence level: Mainly used to indicate the accuracy and reliability of a rule.

$$confidence\left(X => Y\right) = \sup per\left(X \cup Y\right) / \sup per\left(X\right) = P\left(Y \mid X\right) \tag{12}$$

The Apriori algorithm is performed using an iterative method of layer-by-layer search, i.e., using the set of k items to find the set of $(k+1)$ items, thereby exhausting all frequent item sets. The process is as follows:

① Iterate to find the set of frequent single-item sets $L1$.

② Use $L1$ to find the set of frequent 2-item sets $L2$, and similarly use $L2$ to find the set of frequent 3-item sets $L3$.

③ Continue until no frequent k-item sets are found. Each Lk requires one database scan.

Combining the application of $C-P$ similarity between community users discussed earlier in this paper, the main idea of this algorithm is: compare and analyze the resources occupied by each community core user with those of the target user. The resources of other users most similar to those of the target user can then be used as recommendation results for the target user.

2) Resource recommendation based on user reviews

By obtaining the scores given by community core users for resources not used by the target user, and then multiplying these scores by the similarity between the target user and the community core user, we can obtain an approximate predicted score for the target user's evaluation of the resource. Among these, the overall evaluations of the resource by other users with high similarity to the target user will contribute more significantly. Additionally, it is important to consider that resources with more evaluations will have a greater impact on the results. To address this issue, the final predicted rating for the target user can be calculated by dividing the total sum of all other core community users' ratings for the resource by the sum of their similarity scores.

3.3 Experimental validation analysis

3.3.1 Experimental setup

To evaluate the practical application effectiveness of peer-based psychological self-regulation methods optimized using AI algorithms, we selected two algorithms for experimental comparison: an information recommendation algorithm based on community core users and a data mining algorithm based on deep ensemble learning (Method 1), and a resource recommendation algorithm based on improved collaborative filtering (Method 2). A total of 20,000 learning resource data points were selected as the experimental subjects, with 10,000 used for detection rate testing and 10,000 for time testing.

Learning resource data was selected as test data, with m abnormal data points included in the experimental data. The time and speed of the three algorithms in detecting abnormal data were compared to validate the efficiency of the recommended algorithm.

3.3.2 Experimental Results

Generally, the higher the detection rate of abnormal learning resources, the more abnormal data the method detects, and the better the detection results. The detection performance of learning resource anomalies is shown in Figure 3. As the amount of experimental data increases, the detection rates of the three algorithms decrease. Throughout the testing process, the proposed algorithm achieved the highest detection rate of 92.61% when the number of resource data points was 900, and the lowest detection rate of 88.56% when the number of resource data points was 8,100. The overall fluctuation remained within 4.05%, indicating a relatively stable detection rate.

The highest detection rate for the deep ensemble learning algorithm was achieved when the number of resource data points was 1,800, at 75.53%, while the lowest detection rate was achieved when the number of resource data points was 10,000, at 47.38%, with a fluctuation of up to 28.15%.

The highest detection rate for the collaborative filtering personalized recommendation algorithm was 67.42% when the resource data was 4,800, and the lowest was 53.11% when the resource data was 10,000, with a fluctuation of 14.31%.

Among the three algorithms, the recommended algorithm in this paper had the highest detection rate and the best performance. The collaborative filtering personalized algorithm had the lowest detection rate and the worst performance.

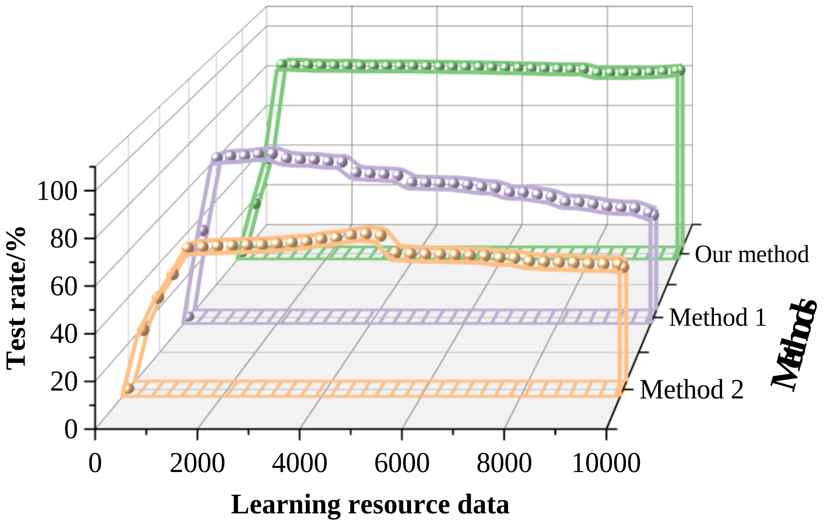


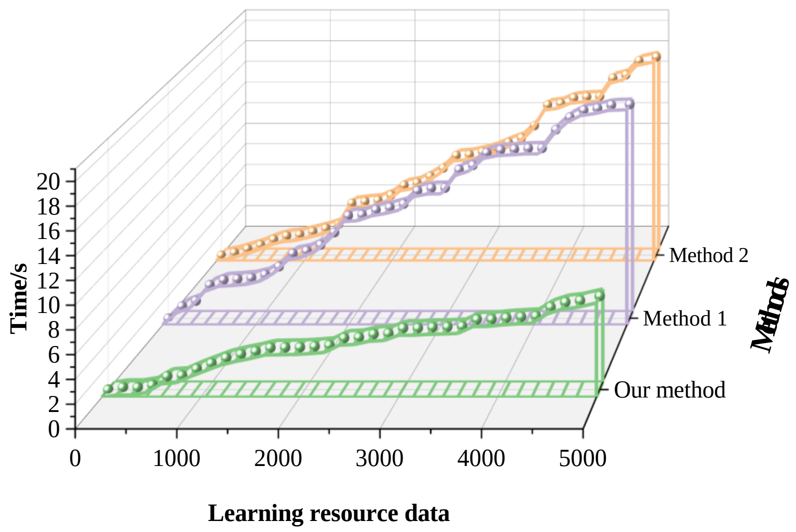
Figure 3: Learning resource anomaly data test effect

Experimental testing has demonstrated that the detection rate of the algorithm proposed in this paper is higher than that of deep learning-based ensemble algorithms and collaborative filtering-based personalized recommendation algorithms. However, a high detection rate does not fully represent the efficiency of the recommendation algorithm proposed in this paper. Therefore, it is also necessary to test the detection speed of the algorithm proposed in this paper. A detection runtime comparison experiment was set up, which was conducted in two stages: 0–5,000 and 5,000–10,000 learning resource data detection runtime tests, to ensure the accuracy and authenticity of the test. A shorter runtime indicates faster detection speed and higher efficiency. The specific detection runtime is shown in Figure 4, where (a) and (b) represent the runtime for the first and second stages, respectively. The runtime of all three algorithms increases as the amount of data increases. When the number of resource data points is 0–5,000, the runtime of the proposed recommendation algorithm is 0–7.83 seconds. When the number of resource data points is between 5,000 and 10,000, the runtime is between 7.83 and 11.71 seconds.

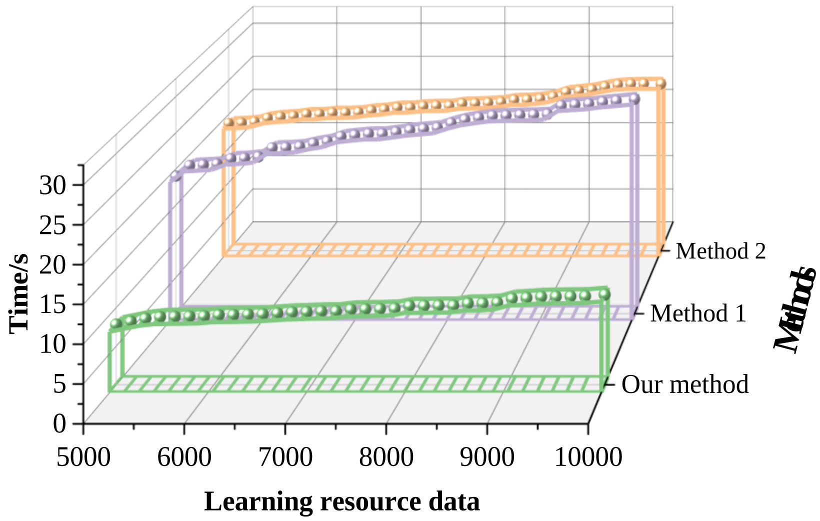
The deep integrated learning algorithm has a runtime of 0 to 19.03 seconds when the number of resource data points is between 0 and 5,000. When the number of resource data points is between 5,000 and 10,000, the runtime is between 19.03 and 29.66 seconds.

The collaborative filtering personalized recommendation algorithm has a runtime of 0–18.69 seconds when the number of resource data points is 0–5,000. When the number of resource data points is 5,000–10,000, the runtime is 18.69–24.49 seconds.

Overall, the information recommendation algorithm based on community core users in this paper has the shortest runtime and the most gradual increase in runtime. Therefore, the detection rate and effectiveness of the recommendation algorithm in this paper are superior to those of the deep ensemble learning algorithm and the collaborative filtering personalized recommendation algorithm.



(a) First stage



(b) Second stage

Figure 4: Learning resource exception data detection operation time

4 The effectiveness of peer psychological counseling self-regulation methods

In the preceding section, the study proposed an AI algorithm-based optimization strategy for emotional communication in peer counseling within social networks. Therefore, this section designs an experiment to test the effectiveness of this peer counseling self-regulation method.

4.1 Objects and Methods

4.1.1 Research subjects

This paper takes a certain university as an example, which has established a relatively well-developed peer counseling model.

(1) Individual interviews: Using a self-designed peer counseling self-regulation method satisfaction interview outline, 20 peer counselors who had undergone training in peer counseling self-regulation methods were interviewed to understand their satisfaction with the peer counseling self-regulation methods.

(2) Quasi-experimental study: 40 peer counselors were voluntarily divided into an experimental group and a control group. After two months of training, they participated in a university-level peer counseling competition, and the results of the two groups were compared. The experimental group consisted of 20 participants who engaged in one hour of group training per week, practicing with both real individuals and the peer counseling self-regulation method. During their free time, the experimental group independently used the peer counseling self-regulation method for further learning. The control group of 20 participants followed a traditional training model, engaging in one hour of simulated training with real people each week, and independently learning peer counseling techniques through reading during their free time.

(3) Survey changes in students' mental health levels, the efficiency of mental health promotion and science popularization activities, and the number of campus mental health crises before (2023) and after (2024) the implementation of peer counseling self-regulation methods optimized using AI algorithms.

4.1.2 Research Tools

(1) 90-item Symptom Checklist (SCL-90): Used to assess changes in students' mental health before and after the implementation of peer counseling self-regulation methods.

(2) Ma's Generalized Scale of Burnout: Used to assess peer counselors' levels of occupational burnout.

(3) Peer Counseling Status Survey Questionnaire: This is a self-designed survey questionnaire primarily used to assess students' attitudes toward mental health, satisfaction with peer counseling services, and willingness to seek help.

4.1.3 Statistical methods

Questionnaire data were processed using SPSS 22.0 software. Normally distributed quantitative data are expressed as x ± s. Intergroup differences were compared using t-tests. Count data are expressed as frequencies and percentages. Intergroup differences were compared using x^2 tests. A P value < 0.05 was considered statistically significant.

4.2 Analysis of Results

4.2.1 Comparison of Professional Competencies

The test results showed that peer counselors who received training in peer counseling self-regulation methods scored significantly higher in the competition than those who did not receive training (P < 0.05), with a 39.62% increase in scores. A comparison of scores between the two groups in the school-level peer counseling competition is shown in Table 1, where * indicates P < 0.05. Peer counselors in the experimental group were able to proficiently apply peer counseling self-regulation methods in online counseling, which helped them better understand and address students' psychological needs and provide more effective offline psychological support.

Table 1: Peer psychological coaching game scores(x±s)

Group	Number	Score	*t*
Control group	20	126.02±25.14	-2.028*
Experimental group	20	175.95±20.63	

4.2.2 Comparison of the number of psychological crises

A chi-square test was conducted on the data regarding the occurrence of various psychological crises among students before and after the implementation of the proposed method. The comparison of the number of occurrences of various crises is shown in Table 2, with *** indicating P < 0.001. The peer psychological counseling self-regulation method had a positive impact on the school's psychological safety work, with a significant decrease in the total number of psychological crisis incidents, from 140 in 2023 to 77 in 2024 (P < 0.001), representing an overall decrease of 45%.

Table 2: Comparison of the number of crises

Crisis	2023	2024	x^2
Primary crisis number	76	54	
Secondary crisis number	30	14	
Third crisis number	34	9	
Total number	140	77	198.512***

4.2.3 Comparison of Mental Health Levels

An independent samples t-test was conducted on the SCL-90 scores of students in 2023 and 2024. The comparison of SCL-90 data between students in 2024 and 2023 is shown in Table 3. After the widespread promotion of peer psychological counseling self-regulation methods, the overall mean score of SCL-90 decreased by 7.53%, and students' mental health levels improved significantly (P < 0.001).

Table 3: Comparison of SCL-90 data in 2023 and 2024(x±s)

Factors	2024(x±s)		2023(x±s)		*t*
Somatization	1.26	0.43	1.33	0.51	-6.913***
Compulsion	1.57	0.58	1.69	0.64	-5.342***
Interpersonal sensitivity	1.45	0.54	1.55	0.68	-8.234***
Depression	1.39	0.51	1.48	0.63	-10.503***
Anxiety	1.29	0.48	1.42	0.55	-7.742***
Antagonism	1.32	0.36	1.43	0.44	-8.329***
Horror	1.34	0.35	1.46	0.47	-10.787***
Paranoia	1.29	0.42	1.38	0.56	-10.701***
Insanity	1.25	0.37	1.36	0.43	-7.221***
Other	1.34	0.35	1.45	0.41	-6.547***
Total	121.42	0.39	132.25	0.48	-7.859***
Mean	1.35	0.45	1.46	0.53	-9.303***
Positive number	21.32	20.47	26.52	24.54	-7.101***

4.2.4 Comparison of Job Burnout Levels

An independent samples t-test was conducted to compare the levels of occupational burnout between the two groups of peer counselors. Table 4 shows the comparison of occupational burnout levels between the two groups. Peer counselors who used self-regulation methods had significantly lower levels of occupational burnout than those who did not ($P < 0.001$), with a reduction of 20.52%.

Table 4: The comparison of the burnout degree in the two friends groups(x±s)

Group	Number	Score	*t*
Unused	20	54.74±17.25	1.654***
Used	20	43.51±13.48	

4.2.5 Comparison of Satisfaction and Awareness of Assistance

An independent samples t-test was conducted to compare the satisfaction levels and help-seeking awareness of peer counseling between the two groups of students. The results are presented in Table 5. The results showed that students who frequently experienced peer counseling self-regulation methods had significantly higher help-seeking awareness and satisfaction with peer counseling than those who had never experienced peer counseling self-regulation methods ($P < 0.001$), with satisfaction and help-seeking awareness increasing by 111.18% and 73.14%, respectively.

Table 5: The two groups psychological counseling satisfaction and the help awareness (x±s)

Group	Number	Help awareness	Satisfaction	*t*
Unused	20	1.52±0.89	1.75±0.82	11.552***
Used	20	3.21±1.34	3.03±1.04	13.227***

5 Conclusion

Peer group psychological counseling relies on school resources to carry out its work and has significant practical significance as an effective supplement to college students' mental health education courses. This study designs community mining methods and information recommendation algorithms based on community core users to construct a peer psychological counseling self-regulation method in social networks. The resource recommendation effect of this method is analyzed, and a comparison experiment is set up to verify the effectiveness of the peer psychological counseling self-regulation method.

(1) Compared to other recommendation algorithms, the detection rate of the method proposed in this paper reaches up to 92.61%, which is 17.08% and 25.19% higher than the comparison methods. The detection rate fluctuates within 4.05%, and the overall running time is 0–11.71 seconds. This indicates that the information recommendation algorithm based on community core users proposed in this paper has a higher detection rate and lower detection running time, demonstrating its superior effectiveness.

(2) Students who adopted the peer counseling self-regulation method showed significant improvements in peer counseling competition performance, peer counseling satisfaction, and help-seeking awareness ($p < 0.001$), with increases of 39.62%, 111.18%, and 73.14%, respectively. Additionally, after implementing the peer counseling self-regulation method, the frequency of crises, students' SCL-90 scores, and peer counseling burnout levels all decreased significantly ($p < 0.001$), by 45%, 7.53%, and 20.52%, respectively, indicating the proposed method's promotional effects on peer counseling emotional transmission and student mental health.

Peer group counseling is a beneficial practice for addressing college students' psychological issues based on their psychological strengths. Peer group counseling targets common psychological issues among college students, effectively mitigating the impact of insufficient mental health professionals in higher education institutions. Additionally, it enhances students' mental health literacy and maintains campus safety and stability.

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