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Construction of knowledge sharing network indicator system for medication therapy management service training teams based on social network analysis

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Abstract

Background Based on the perspective of social network theory, this study explored the network indicator system that facilitated optimal knowledge sharing effect in Medication Therapy Management Services (MTMS) training teams. The aim was to provide a reference for optimizing MTMS training and improving training quality.

Methods Utilizing social network analysis combined with a questionnaire survey, a knowledge sharing matrix for MTMS training teams was constructed. Knowledge sharing behavior was assessed from three perspectives: individual networks, whole networks, and cohesive subgroups.

Results Individual network analysis showed that the knowledge sharing effect within the training team reached its peak when the out-degree centrality was ≥ 3.5, in-degree centrality was ≥ 2.5, eigenvector centrality was ≥ 0.065, and closeness centrality was ≥ 7.86. Whole network analysis indicated that the optimal knowledge sharing effect occurred when the network density of the training team was higher than 0.0343 and the training size was less than 117 participants. Cohesion subgroups analysis demonstrated that knowledge sharing was more effective when members with similar working years participated in training together.

Conclusions The knowledge sharing indicator system developed for MTMS training teams, based on social network analysis, can assist in optimizing the MTMS training model and improving training effectiveness.

Keywords Social network analysis, Medication Therapy Management Services, Knowledge sharing, Network indicator system

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Introduction

In recent years, China's rapidly aging population has led to a significant increase in the incidence of chronic diseases. According to statistics from the National Health Commission, by the end of 2018, there were over 190 million elderly individuals in China suffering from chronic diseases, with the associated disease burden attributable to these conditions exceeding 70% [1]. This trend has not only challenged individual health but also placed new demands on the entire healthcare system. In 2017, national policies mandated that secondary and higher-level hospitals achieve 100% coverage of pharmaceutical services. Clinical pharmacists were mandated to provide patients with personalized and rational medication guidance services. The policies have promoted the growing importance of pharmacists in healthcare teams.

Currently, the field of clinical pharmacy in China is transitioning from drug-centered to patient-centered [2–4]. In response to this change, an increasing number of clinical pharmacists are focusing on Medication Therapy Management Service (MTMS) training [5–7]. Participating in MTMS training is seen as a crucial pathway to enhancing pharmaceutical service capabilities [8]. In March 2017, China Pharmaceutical University and Nanjing Drum Tower Hospital jointly undertook a training program on MTMS. Despite the initiative, there were still some issues that seriously affected the effectiveness and quality of the training. Notably, the insufficient sharing of training content among participants was a major concern.

Knowledge sharing refers to the process where individuals or organizations share their owned knowledge, including information, skills, and experiences, with others [9, 10]. Research on knowledge management has shown that the sharing and transmission of knowledge within an organization largely depends on the social relationship networks within the organization [11]. In this context, social network analysis has been widely used as a powerful research methodology [12]. Wiemken employed social network analysis to assess the knowledge sharing network among infection preventionists in Kentucky hospitals. The results revealed that the knowledge sharing network with low network density and less communication, which undermined effective knowledge sharing [13]. Similarly, Kate Sabot used structured tools to input, analyze, and visualize interview data from 160 employees across eight primary healthcare units. Her analysis obtained detailed data on network elements and proposed effective methods to promote information exchange within the network [14].

However, existing research has mainly focused on calculating social network indicators [15], with limited systematic exploration of the relationship between these indicators and actual knowledge sharing effectiveness. To address this gap, this study employed social network analysis methods to evaluate MTMS training organizations. By quantifying social network indicators, the study further assessed their relationship with knowledge sharing effectiveness, constructing a three-level evaluation system for MTMS training teams. This system encompassed individual network, whole network and cohesive subgroup, providing a basis for improving and optimizing future training efforts.

Materials and methods

Participants

The MTMS Phase V training team consisted of 133 individuals, including 110 students (S1 to S110) and 23 teachers (T1 to T23). The participants came from various hospitals across the country, and most of them were unfamiliar with one another, lacking prior interactions and collaborative experiences.

Questionnaire design

We collected the necessary research data through a questionnaire survey. The survey questionnaire consisted of two main parts (Appendix). Questionnaire A collected basic demographic information about the training participants, including gender, age, years of work experience, and job title. Questionnaire B focused on the knowledge sharing among participants during the training process. This part included five questions, with the first three designed to record and analyze the knowledge sharing behavior:

(1) During the training process, when you encounter problems or difficulties in your learning and need help, which teachers or classmates would you consult for help?
(2) During the training process, after seeking help, which teachers or classmates have assisted you?
(3) Whose inquiries among classmates have you voluntarily answered during the training process?

The remaining two questions were designed to gather evaluations and preferences regarding the interactions between teachers and students, as well as among peers within the training program. These questions assisted educators in gaining a comprehensive understanding of students' daily performance and academic levels, thereby providing additional insights for assessing the quality and effectiveness of the training. However, since these questions were not directly related to the core theme of this study, they were not discussed or analyzed in detail in this manuscript.

Network construction

A social network refers to a collection of social actors and their relationships. Structurally, it is composed of nodes (representing actors) and edges (representing relationships between these actors). In the MTMS training team, each person functioned both as a knowledge provider and as a knowledge recipient. Knowledge sharing occurred through consultation and interactions among team members. A network relationship matrix for the MTMS training team was constructed based on survey questionnaire results. Rows and columns of the matrix represented all students and teachers in the training team, respectively. Elements within the matrix indicated whether knowledge sharing behaviors existed between members. For instance, if member i sought help from member j when encountering difficulties, the position (i, j) in the matrix was marked as 1; if no knowledge sharing occurred between two members, it was marked as 0. Through the matrix, the relationship between nodes can be further analyzed, which can lead to an in-depth understanding of the individual network, whole network, and cohesive subgroup characteristics of the social network.

Criteria for assessing knowledge sharing effectiveness

We analyzed the effectiveness of knowledge sharing within the MTMS training team using core-periphery theory. The team members were categorized into two groups: "good knowledge sharing effectiveness (Group A)" and "poor knowledge sharing effectiveness (Group B)."

The core-periphery theory, originally proposed by American geographer John Friedmann to explain patterns of spatial evolution in regions, has since been widely applied in various fields. This theory can divide network nodes into core and peripheral areas based on the closeness of node connections. In a network, core regions exhibit dense connections [16], while peripheral regions have sparse connections [17, 18]. Core nodes occupy a more important position in the network and play a significant role in knowledge sharing activities. In contrast, peripheral nodes typically have weak connections with other members and have low influence and participation in the knowledge-sharing network. Stewart SA analyzed the knowledge-sharing behaviors of members in clinical online forums and found that core-periphery analysis can effectively identify central members in social networks. Moreover, these central members dominated knowledge sharing activities [19].

Therefore, in this study, members in the core area were considered to have better knowledge sharing, categorized as Group A. Members in the peripheral area were considered to have poor knowledge sharing, categorized as Group B.

Research design

This study collected data on knowledge sharing behaviors within the training program through questionnaire surveys, leading to the establishment of the corresponding social relationship network. Following the construction of this network, Receiver Operating Characteristic (ROC) curve analysis was employed to examine the relationship between individual network indicators and knowledge sharing effectiveness, as well as to determine the optimal threshold for these indicators. After identifying the optimal individual network indicators, the research optimized the density and scale of the whole network. Finally, cohesive subgroup models were utilized to identify tightly connected groups within the social network. The analysis focused on the relationship between the characteristics of members in each cohesive subgroup and knowledge sharing effectiveness, providing a theoretical basis for the grouping strategy in the training program.

Ultimately, a knowledge sharing network evaluation indicator system for the MTMS training team was developed to further enhance training quality (Fig. 1).

Statistical methods

The MTMS training network relationship matrix was established based on the results of the questionnaire survey. Core-periphery analysis, individual network indicators, whole network density, and the identification of cohesive subgroups were calculated using UCINET 6.0 software.

Continuous variables were expressed as median (interquartile range). Discrete variables were expressed as n (%). The Mann–Whitney U test was used to assess differences in individual network indicators between groups with varying knowledge-sharing effectiveness. The Fisher exact test and Kruskal–Wallis H test were employed to examine differences in gender, job title, and years of work experience among cohesive subgroups. Statistical analyses were conducted using IBM SPSS Statistics software version 22.0. P-value < 0.05 was considered statistically significant.

GraphPad Prism 9.5 software was used to plot ROC curves to investigate the association between individual network indicators and knowledge sharing effectiveness. A diagnostic effect was considered better when the Area Under Curve (AUC) > 0.7; the closer the AUC was to 1, the higher the diagnostic value. The optimal threshold was identified based on the maximum Youden's index (Youden's index = sensitivity + specificity—1).

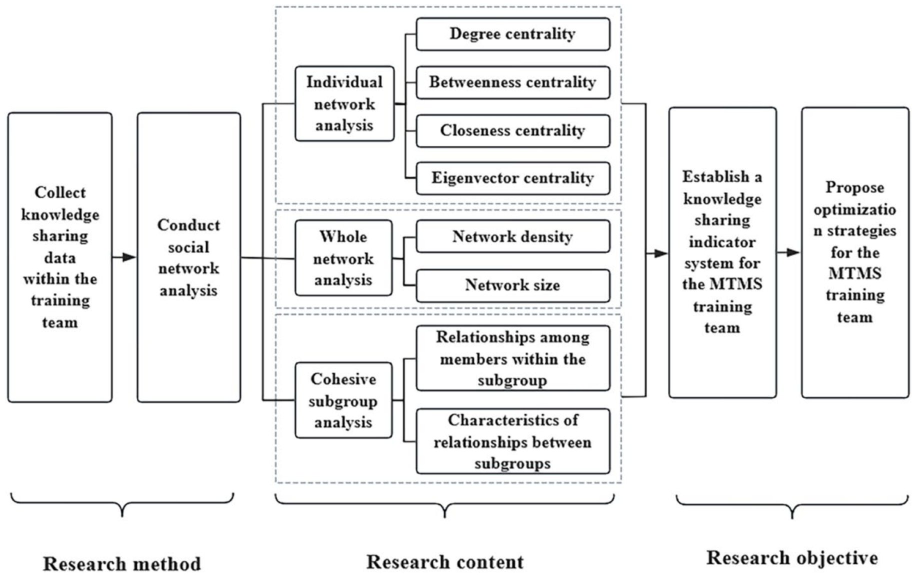

Fig. 1 Research approach and process of this study

Results

Network visualization results

The knowledge sharing relationship diagram in the training network was generated using Netdraw software (Fig. 2). In this diagram, each circular node represented a member, and the directed lines between nodes indicated consultation relationships. Nodes pointed to by arrows signified that they were the recipients of consultation. It can be observed that members at the center were connected to more nodes, while members in the periphery were connected to fewer nodes. Additionally, ten nodes in the network did not have any connection and were called completely isolated nodes.

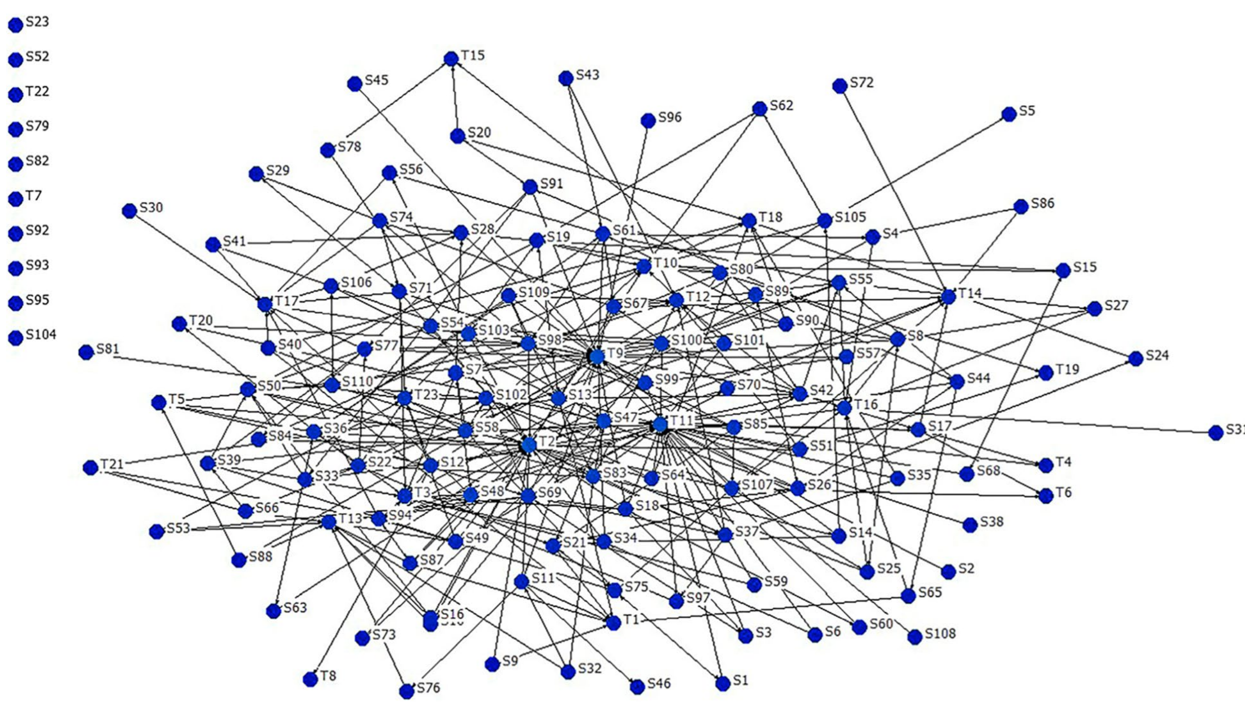

Fig. 2 Knowledge sharing network diagram of the Phase V MTMS training program

Analysis of individual network indicators

Knowledge sharing effectiveness grouping

The analysis revealed 50 members in the core area (Group A) and 83 members in the peripheral area (Group B). There was a significant difference ($P < 0.01$) in individual network indicators between the two groups, as shown in Table 1.

Centrality measures evaluated the importance of nodes from various perspectives. Theoretically, nodes with high values in degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality have more significant influence and occupy advantageous positions. Such nodes are likely to acquire new knowledge earlier and facilitate more effective knowledge sharing [19–21].

The results showed that the degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality in Group A were higher than those in Group B, which indicated that the members of Group A occupied the core positions in the network, leading to more frequent knowledge sharing and faster knowledge circulation.

Optimal threshold value

ROC curves were plotted using individual network indicators as diagnostic measures and the binary variable of member knowledge sharing effectiveness as the outcome measures (Fig. 3). The optimal thresholds, AUC, Youden's index, sensitivity, and specificity corresponding to each indicator were shown in Table 2.

The study found that for individuals, when out-degree centrality was ≥ 3.5, in-degree centrality was ≥ 2.5, eigenvector centrality was ≥ 0.065, and closeness centrality was ≥ 7.86, the knowledge sharing effectiveness of members was exemplary.

Performance analysis

The study investigated the association between knowledge sharing effectiveness and members' academic performance. Differential analysis revealed that the performance of Group A members was 99.39 (95.23, 100.00), while Group B members had a performance of 95.53 (84.70, 99.28). The difference in performance between the two groups was significant ($P < 0.05$), indicating that members with higher academic performance had a better knowledge sharing effectiveness. Using academic performance as a diagnostic measure to assess knowledge sharing effectiveness among members, the results indicated that academic performance demonstrated good diagnostic value for members' knowledge sharing effectiveness (AUC > 0.7). Specifically, members whose academic

Table 1 Network centrality analysis

Project	Out-degree centrality	In-degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality
Group A	4.00 (1.00, 6.25)	3.00 (1.00, 6.25)	85.42 (0.00, 398.04)	8.029 (7.90, 8.13)	0.10 (0.06, 0.13)
Group B	2.00 (0.00, 3.00)	1.00 (0.00, 2.00)	0.00 (0.00, 73.33)	7.774 (7.56, 7.91)	0.04 (0.01, 0.06)
Z	-3.954	-5.081	-2.607	-6.952	-7.427
P	0.000	0.000	0.009	0.000	0.000

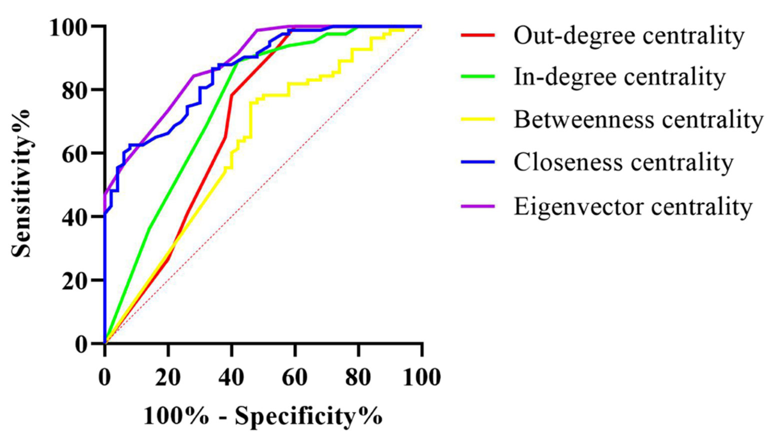

Fig. 3 ROC curve of individual network indicators

Table 2 Optimal threshold values for individual network indicators

Grouping criteria	Diagnostic indicators	Threshold	AUC	Youden's Index	Sensitivity	Specificity
Core-periphery	Out-degree centrality	≥ 3.5	0.7023	0.3831	0.7831	0.6000
	In-degree centrality	≥ 2.5	0.7573	0.4716	0.8916	0.5800
	Betweenness centrality	-	0.6275	-	-	-
	Closeness centrality	≥ 7.860	0.8605	0.5465	0.6265	0.9200
	Eigenvector centrality	≥ 0.065	0.8837	0.5634	0.8434	0.7200

performance exceeded 95.47 demonstrated sufficient knowledge sharing effectiveness.

Analysis of whole network indicators

The whole network indicators included network density, network size, and network centralization [22]. This study explored knowledge sharing within the training team from the perspectives of network density and network size, aiming to improve the effectiveness of knowledge sharing within the training team by optimizing these indicators.

Network density

Network density was defined as the ratio of the total number of existing relationships divided to the theoretical maximum number of relationships. To ensure that knowledge sharing behaviors were fully realized within the training team, the out-degree centrality of each member should reach the optimal threshold, meaning that each member must engage in knowledge sharing behaviors with at least four individuals. The distribution of out-degree centrality within the training network, along with the network density, was presented in Table 3.

Network size

Calculations indicated that to achieve optimal knowledge sharing effectiveness within the training team, the whole network density must be at least 0.0343, with a maximum training size of 117 participants.

Cohesion subgroups analysis

Many social networks exhibit the characteristic of "homophily," where organizations tend to establish relationships with others that are similar to themselves [23]. This study aimed to investigate how individual characteristics (gender, professional title, years of work experience) influence the formation of cohesion subgroups and the relationships of knowledge sharing within these groups. Additionally, the study sought to determine the correlation between the knowledge sharing effects and the commonality among group members, providing a theoretical basis for the subsequent phase of pedagogical training subgroups.

Blockmodels analysis

The MTMS Phase V training members were divided into eight groups using the convergence of iterated correlation (CONCOR) method, and the density matrix was shown in Table 4. When the density of a cohesive subgroup was higher than the whole network density, it indicated that the nodes within the cohesive subgroup were well-connected and exhibited high levels of knowledge sharing. The association characteristics between groups were illustrated using the Netdraw software, as shown in Fig. 4. Each circular node represents a group, and lines indicate close connections between two groups.

This study observed that each node within Groups 1, 2, 5, 6, 7, and 8 had at least two connections, indicating that communication and knowledge sharing were more frequent and substantial among these six groups. The internal density of Group 2 and Group 7 was higher than the whole network density, suggesting better sharing effects within these groups. In contrast, Group 3 and Group 4 had an internal density of 0 and limited communication with other groups, indicating poor knowledge sharing effectiveness.

Table 3 Statistical distribution of out-degree centrality in the training team

Condition		Out-degree centrality											Network density
		0	1	2	3	4	5	6	7	8	9	10	
Actual network	Number	32	15	26	12	19	9	8	5	5	1	1	**0.0208**
Ideal network	Number	-	-	-	-	104	9	8	5	5	1	1	**0.0343**

Analysis of group member composition

Since group 3 was utterly isolated, group 4 had only one directed edge, resulting in a network density of 0 for both groups, these two groups were deemed less effective in knowledge sharing. Consequently, they were merged in the individual characterization study.

The gender and professional title between groups were tested using the Fisher's exact tests, while years of working experience were tested using Kruskal–Wallis H tests. However, none of the differences were statistically significant ($P>0.05$), as shown in Tables 5 ~ 6.

Discussion

Social network indicators analysis and significance

Individual network

To establish reference standards for individual network indicators of members within the MTMS training team, a ROC curve was plotted to predict the knowledge sharing

Table 4 Density matrix of cohesive subgroup models

Groups (number)	1	2	3	4	5	6	7	8
1 (24)	0.011	0.003	0	0.01	0.004	0.003	0.002	0
2 (14)	0	0.077	0	0	0.004	0.009	0.018	0.014
3 (10)	0	0	0	0	0	0	0	0
4 (4)	0.052	0	0	0	0	0.016	0.010	0
5 (20)	0.083	0.011	0	0.013	0.016	0.019	0.017	0.007
6 (16)	0.156	0.027	0	0	0.031	0.013	0.016	0.009
7 (24)	0.089	0.036	0	0	0.008	0.016	0.022	0.012
8 (21)	0.085	0.044	0	0	0.007	0.015	0.014	0.007

Each element in the matrix represents the connection density between two subgroups, defined as the ratio of the actual number of connections to the maximum possible connections

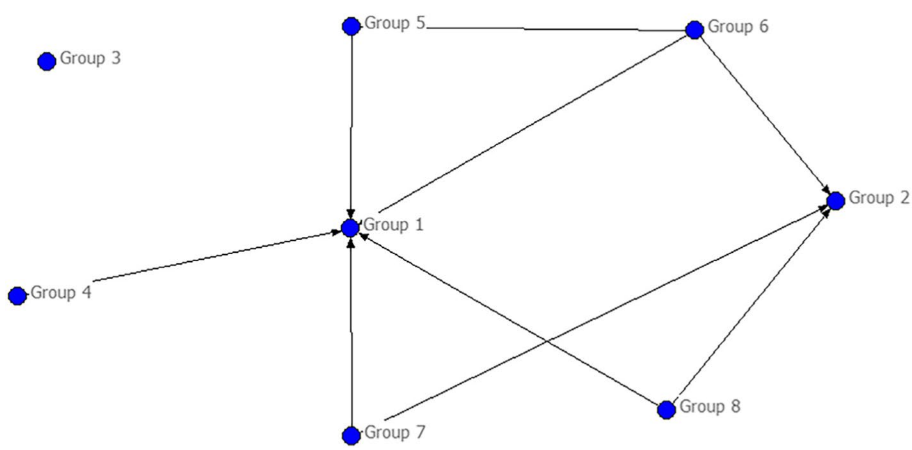

Fig. 4 Characteristics of relationships between groups

Table 5 Comparison of gender and professional titles among members of groups

Project		1 *n* (%)	2 *n* (%)	3&4 *n* (%)	5 *n* (%)	6 *n* (%)	7 *n* (%)	8 *n* (%)	*P*
Gender	Male	12 (50.0)	4 (28.6)	5 (35.7)	4 (20.0)	3 (18.8)	6 (25.0)	4 (19.0)	0.258
	Female	12 (50.0)	10 (71.4)	9 (64.3)	16 (80.0)	13 (81.2)	18 (75.0)	17 (81.0)	
Professional title	Senior	7 (29.2)	7 (50.0)	8 (57.1)	5 (25.0)	8 (50.0)	6 (25.0)	7 (36.1)	0.229
	Intermediate	16 (66.7)	6 (42.9)	5 (35.7)	9 (45.0)	6 (37.5)	16 (66.7)	12 (52.6)	
	Junior	1 (4.2)	1 (7.1)	1 (7.1)	6 (30.0)	2 (12.5)	2 (8.3)	2 (11.3)	

Table 6 Comparison of years of working experience among members of groups

Group	Number	Years of working experience		χ2	*p*
		Average	Standard deviation		
1	24	12.54	9.09	7.634	0.266
2	14	11.50	5.14		
3&4	14	17.07	9.72		
5	20	9.35	4.75		
6	16	14.19	7.87		
7	24	11.13	6.08		
8	21	13.14	7.12		

effectiveness based on network indicators, and their AUC values were calculated. The study found that when the core-periphery analysis was used to judge knowledge sharing effectiveness, out-degree centrality, in-degree centrality, closeness centrality and eigenvector centrality demonstrated superior diagnostic value. Although there was a significant difference in betweenness centrality between Group A and Group B, it cannot be used as a predictive indicator of the effectiveness of knowledge sharing among members. Possible explanations are as follows.

Betweenness centrality measures the importance of a node in a network by assessing its role as a connection path [24]. Generally, nodes located in core areas exhibit higher betweenness centrality. However, in the MTMS training network, it was found that some nodes situated in the core area, although receiving many inquiries from other nodes, did not themselves play the role of transferring information from one node to another. In other words, despite many other nodes pointing to them, these nodes did not act as significant intermediaries for information transfer within the network, resulting in lower betweenness centrality. This behavioral pattern revealed potential bottlenecks in knowledge sharing within the network and posed new challenges and requirements for our training programs.

The MTMS training network contained ten isolated nodes without any connection (completely isolated nodes). Calculating closeness centrality in such cases presented unique challenges. Closeness centrality typically measures the inverse of the average shortest path length from a node to all other nodes [25]. If the sum of the shortest path lengths from a node to other nodes is exceptionally large, its closeness centrality becomes very small, approaching zero. In the extreme case, if a node cannot reach any other nodes, the calculation results in an infinite distance, making the closeness centrality measure invalid. Therefore, in this study, their Closeness Centrality was defined as 0.

The study aims to establish a comprehensive evaluation indicator system to judge the effectiveness of knowledge sharing among members from different perspectives. Although the existence of completely isolated nodes introduced some interference to the research results, closeness centrality was retained as a predictive indicator to evaluate the effectiveness of knowledge sharing among members. This approach allowed for a thorough assessment of the influence and knowledge sharing impact of each node in the network. In addition, other indicators such as degree centrality, betweenness centrality, and eigenvector centrality were utilized to provide a a multi-dimensional perspective.

Whole network analysis

Network density was used to characterize the extent of interconnections among nodes within a network [26]. A higher density indicated closer relationships between members, which in turn enhanced the effectiveness of knowledge sharing within the training team. Network size refers to the total number of participants in the training team. Given that each actor has limited resources and capabilities to establish and maintain relationships, network size was crucial for the structure of social relations [21]. An appropriate size can improve the effectiveness of knowledge sharing within the training team.

Currently, 85 members in the training team did not reach the optimal threshold for out-degree centrality values, indicating that most members lacked proactive communication. The lack of individual sharing behavior would affect the whole network density. Although the network density of Phase V (0.0208) was already higher than that of Phase IV (0.0202), it still had not reached the optimal sharing standard.

Cohesion subgroups analysis

Due to the large number of participants in the training program, members were initially divided into different groups to ensure interactive teaching and teaching quality. Research has shown that group-based learning contributes to improving academic performance, communication skills, and clinical outcomes while enhancing learners' engagement, motivation, and satisfaction [27, 28]. In previous MTMS trainings, this grouping was random, and the research aims to find a more rational grouping method to promote knowledge sharing among members within the group [10].

In social network analysis, when relationships between specific nodes are so close that they form a sub-group, such groups are referred to as cohesive subgroups [29]. The study analyzed the composition of members within cohesive subgroups, aiming to uncover the relationship between the effectiveness of knowledge sharing and the commonalities among members within the group, thereby providing a theoretical basis for grouping in the next phase of teaching and training. Unfortunately, there were no significant differences in gender, professional titles, or years of experience among the subgroups.

Although the overall distribution of years of work experience did not differ significantly among the groups, Groups 3 & 4 had notably higher average years of work experience compared to the other six groups. On the contrary, Groups 2 and Groups 7 had lower average years of work experience with smaller standard deviations. This may be attributed to the following reasons: (1) Members with more years of work experience had poorer sharing effects; (2) Members with similar years of work experience were more likely to form a group spontaneously, resulting in better knowledge sharing within the team.

Members with similar years of experience were more likely to establish connections, which may have been related to the social and psychological benefits provided by peer mentoring [30] and professional development [31]. They often faced common challenges and needs [32–34], and this similarity may have facilitated their interactions [23]. Therefore, in future training sessions, years of experience could be considered as a criterion for grouping participants.

Suggestions for optimizing knowledge sharing effects in MTMS training team

Based on the research findings, there were three main directions for optimizing the MTMS training team in the future:

(1) Individual Level: Currently, only 36% of the members in the training team had out-degree centrality ≥ 3.5, 29% had in-degree centrality ≥ 2.5, 37% had eigenvector centrality ≥ 0.065, and 58% had closeness centrality ≥ 7.86. These numbers indicated that knowledge sharing behaviors were not sufficient. In the future, the training team should focus on enhancing and reinforcing mutual education among the training members.

(2) Whole Network Level: The actual number of members in phase V of the training team was 133, but the ideal number should be controlled within 117. Reducing the number of members appropriately may facilitate knowledge sharing within the training team and improve network density.

(3) Cohesive Subgroup Level: Dividing members with similar years of experience into the same group may facilitate knowledge sharing within the groups. Furthermore, it was observed that members with higher years of working experience tend to exhibit lower knowledge sharing effects.

This study employed social network analysis to evaluate the impact of knowledge sharing in the MTMS training team from three perspectives: individual analysis, whole analysis, and Cohesive subgroup analysis, as detailed in Table 7.

Limitation

The knowledge sharing questionnaire was only distributed to the students, which might lead to the omission of certain edges in the actual network, potentially affecting the comprehensive analysis of the knowledge sharing network. Future research will aim to refine the design of the questionnaire to address this limitation and ensure a more complete representation of the network.

Table 7 Evaluation indicators for knowledge sharing effectiveness of MTMS training teams

Primary indicators	Secondary indicators	Specific data
Individual network indicators	Out-degree centrality	Out-degree centrality ≥ 3.5
	In-degree centrality	In-degree centrality ≥ 2.5
	Betweenness centrality	——
	Closeness centrality	Closeness centrality ≥ 7.86
	Eigenvector centrality	Eigenvector centrality ≥ 0.065
Whole network indicators	Network density	Whole network density ≥ 0.0343
	Network size	Network size ≤ 117
Cohesive subgroup analysis	Member years of working experience	Members with lower years of working experience tend to have better knowledge sharing effectiveness
	Composition of members within the group	When students with similar years of working experience are grouped together, they exhibit better knowledge sharing effectiveness within the group

Conclusion

The standardized training for clinical pharmacists is gradually being implemented worldwide [35–37], and the evaluation of clinical pharmacist training further promotes their continuous education and professional development [38]. This study evaluated the knowledge sharing effectiveness within MTMS training teams from the perspective of social network analysis, focusing on the individual network, whole network, and cohesive subgroups, and proposes improvement measures. It is hoped that this study can provide a new perspective to knowledge sharing research and provide empirical support for knowledge management and educational training in practice.

Appendix

Questionnaire A

(1) What is your full name?
(2) What is your gender?
(3) What is your academic or professional title?
(4) How many years of working experience do you have?

Questionnaire B

(1) During the training process, when you encounter problems or difficulties in your learning and need help, which teachers or classmates would you consult for help? (Please fill in the names of teachers or classmates.)
(2) During the training process, after seeking help, which teachers or classmates have assisted you? (Please fill in the names of teachers or classmates.)
(3) Whose inquiries among classmates have you voluntarily answered during the training process? (Please fill in the names of teachers or classmates.)
(4) In your opinion, which teachers or classmates in this training program have a solid theoretical foundation and extensive practical experience? (Please fill in the names of teachers or classmates.)
(5) If this training were to rearrange groups, with which classmates would you most prefer to be grouped? (Please fill in the names of classmates.)

Abbreviations

MTMS	Medication Therapy Management Services
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
CONCOR	Convergence of iterated correlation

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Authors' contributions
Jp Z and Wh G were responsible for teaching design and manuscript writing; R T, Wp L and Y Yao analyzed the data, interpreted the results, and wrote the manuscript; Sm Yan, Qh Wu, J Wang and X Yang provided teaching guidance for the research.

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Availability of data and materials
The datasets generated in the current study are available from the corresponding author upon reasonable request.

Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The study protocol was approved by the Nanjing University Medical School, Nanjing Drum Tower Hospital Ethics Committee (2024–401-01). Informed consent was waived by the Nanjing University Medical School, Nanjing Drum Tower Hospital Ethics Committee. The questionnaire content did not involve personal privacy and clearly informed participants of the research purpose; participation was entirely voluntary.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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