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Knowledge transfer between physicians from different geographical regions in China's online health communities

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Abstract
Online Health Communities (OHCs) are a type of self-organizing platform that provide users with access to social support, information, and knowledge transfer opportunities. The medical expertise of registered physicians in OHCs plays a crucial role in maintaining the quality of online medical services. However, few studies have examined the effectiveness of OHCs in transferring knowledge between physicians and most do not distinguish between the explicit and tacit knowledge transferred between physicians. This study aims to demonstrate the cross-regional transfer characteristics of medical knowledge, especially tacit and explicit knowledge. Based on data collected from 4716 registered physicians on Lilac Garden (DXY.cn), a leading Chinese OHC, Exponential Random Graph Models are used to (1) examine the overall network and two subnets of tacit and explicit knowledge (i.e., clinical skills and medical information), and (2) identify patterns in the knowledge transferred between physicians, based on regional variations. Analysis of the network shows that physicians located in economically developed regions or regions with sufficient workforces are more likely to transfer medical knowledge to those from poorer regions. Analysis of the subnets demonstrate that only Gross Domestic Product (GDP) flows are supported in the clinical skill network since discussions around tacit knowledge are a direct manifestation of physicians' professional abilities. These findings extend current understanding about social value creation in OHCs by examining the medical knowledge flows generated by physicians between regions with different health resources. Moreover, this study demonstrates the cross-regional transfer characteristics of explicit and tacit knowledge to complement the literature on the effectiveness of OHCs to transfer different types of knowledge.

Keywords Online health communities · Knowledge transfer · Tacit knowledge · Explicit knowledge · ERGMs

1 Introduction

Advancements in online collaboration tools have given rise to online communities across various sectors. Among these, online health communities have emerged as self-organizing platforms where diverse users (e.g., patients, physicians, and healthcare workers) can freely create, share, disseminate, and exchange information beyond the constraints of time and space [22]. Patients use OHCs to communicate with others, share information, and extend emotional support, while physicians use them to exchange knowledge and ideas related to treatment methods and diagnostic experiences. Notably, developments in OHCs have helped address the imbalance in hygiene procedures to a certain extent [67, 70], which is considered a social value resulting from the creation of OHCs [19].

OHCs provide value to users through knowledge transfer opportunities [11, 72]. Like Communities of Practice (CoP), OHCs allow for collaboration and knowledge exchange between physicians, transcending offline boundaries [34]. Physician-physician collaboration is a key feature of OHCs, which aims to address patients' needs, reducing their uncertainty and anxiety by combining the experiences and knowledge of physicians from around the world [66]. Within OHCs, physicians learn from each other by observing their behaviors, asking questions, and contributing to discussions [47]. Additionally, they share their medical routines

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[65], which helps to transfer and enrich health knowledge and improve the quality of healthcare services delivered to patients [52].

Physicians are a special group of knowledge workers in the healthcare industry with a narrow scope of work who possess the ability to use knowledge to solve practical problems [14]. As such, the knowledge gap in this group reflects the gap in physicians' professional competence. First, the transfer of knowledge between physicians is crucial in improving the quality of online healthcare services [53]. Second, in the face of emerging diseases, such as COVID-19, knowledge transfer between physicians is essential for diagnosis and the identification of treatment options [63]. Third, the cross-regional flow of medical knowledge offers the potential to bridge the knowledge gap among physicians working in different regions and alleviate geographical disparities. These findings underscore the importance of physicians' knowledge transfer in the medical profession.

Extant research has mainly investigated the antecedents and consequences of knowledge transfer among physicians in online and offline contexts [53, 60]. Within the online transfer model, technologies that provide collaboration between remote users has received the greatest attention [68]. OHCs represent a novel information exchange platform that allow physicians to seek and share knowledge, surpassing the limitations of telemedicine. As such, they have become an important platform for physicians to exchange and transfer experiences and medical knowledge, while alleviating the constraints of time and space. Despite the increasing prevalence of OHCs, few studies have empirically examined their role in transferring medical knowledge among physicians. We, therefore, ask our first research question: *Can OHCs support the transfer of medical knowledge between physicians across different regions in China?*

In healthcare, knowledge can be classified as explicit or tacit, both of which play important, but distinct roles [49]. Explicit knowledge, represented by clinical guidelines, is easily accessible through the Internet, while tacit knowledge, represented by personal experiences, is more challenging to transfer but offers greater value [22, 58]. In the healthcare context, physicians can often recall knowledge about diagnosis and treatment from their previous experiences and rely on pre-existing experiences to consider them comprehensively and systematically [25]. Newly qualified physicians entering the workforce may lack experience compared to clinical guidelines while traditional medical settings offer limited access to fellow physicians for gaining such clinical experience. OHCs help in this regard by visualizing and recording tacit medical knowledge, enabling the large-scale transfer of explicit and tacit knowledge [74].

As mentioned earlier, knowledge transfer is critical for physicians. This study, therefore, considers the transfer of tacit knowledge an important part of achieving knowledge transfer in the healthcare industry. First, the quality of medical services delivered by physicians and other healthcare workers largely depends on the physicians' tacit knowledge. Second, tacit knowledge is considered an excellent source of innovation [18]. Third, offline physicians have limited access to tacit knowledge compared to explicit knowledge and, therefore, OHCs offer the possibility of making tacit knowledge explicit, thus enhancing the exchange of tacit knowledge across regions to balance the differences in physicians' competencies. While the first research question may only detect the overall knowledge flow between regions in OHCs, its usefulness for transferring specific types of knowledge has not been tested [8, 10, 44]. This study, therefore, poses the second research question: *What role do OHCs play in tacit and explicit knowledge transfer between physicians from different regions?*

To answer these research questions, we categorize the different types of knowledge transferred by physicians in OHCs based on their geographical regions. Data was collected from 4,716 registered physicians in the Cardiology community on Lilac Garden (www.dxy.cn/bbs/), a leading OHC in China used by physicians and other healthcare professionals. The data collected included physicians' interactions (i.e., posts and replies), department(s), geographical location, and other community characteristics. First, concerning the categorization of geographical regions, prior studies show that health outcomes are strongly linked to human resources and the high density and quality of physicians have a positive effect on outcomes [51, 56, 57, 59]. The quality of physicians in a region is related to the economic level of the region [35] and, therefore, two indicators are used to divide the regions where physicians are located, namely, the healthcare workforce and GDP. Second, we examine the content of physicians' posts to identify whether the knowledge conveyed is explicit or tacit. Specifically, physicians discuss cases in detail and express their diagnostic and treatment opinions in OHCs, and this information about their practice experience is considered tacit knowledge, while the rest of the objective information shared, such as textbooks, pictures, videos, and clinical guidelines, is considered explicit knowledge.

This study models and analyzes the OHC social networks using exponential random graph models with findings revealing a net surplus of total knowledge from regions with sufficient workforces to insufficient ones and developed to less developed regions. To identify tacit and explicit knowledge flows in the network, we focused on two subnets: clinical skills and medical information. Analysis of the two subnets demonstrates that medical information is the same across the overall network while only developed to less developed flows are supported in the clinical skills network; in other words, tacit knowledge is only transferred between regions from high GDP to low, while explicit knowledge can be transferred between regions from high GDP and sufficient resources to low and insufficient. These findings demonstrate that tacit knowledge is more difficult to transfer than explicit knowledge. With regards the clinical skills network, the process of physicians colliding with each other can be reflected. Physicians who have interacted previously will continue to cooperate using a follow-up process, while the general medical information network is mainly used for temporary one-sided help; this finding suggests that tacit knowledge requires richer media for successful knowledge transfer.

This study provides three key contributions to current understanding. First, it contributes to the existing literature on knowledge transfer between physicians in OHCs and demonstrates, through empirical analysis, that medical knowledge flows from superior regions to less superior regions in online platforms. Second, this study shows the interaction network between physicians in OHCs, especially regarding the exchange of tacit and explicit knowledge, and discusses the characteristics of two types of knowledge transfer networks separately to enrich the literature on physicians' online interactions. Third, it examines the effectiveness of OHCs in transferring tacit and explicit knowledge between regions with different human resources, and the features of two different types of medical knowledge in cross-regional transfer to complement the literature on the effectiveness of OHCs in transferring different knowledge.

2 Literature review

2.1 Definitions of medical knowledge types

Nonaka [45] argued that knowledge can be categorized into two types: explicit and tacit. Explicit knowledge is a kind of objective knowledge in formal and systematic language, usually shared in the form of raw data, formulas, specifications, and manuals [28], while tacit knowledge is the result of an individuals' experiences, senses or intuition, and it is highly dependent on context [9]. The classification of explicit and tacit knowledge is based mainly on its economic value and ease of delivery [33]. Generally, tacit knowledge is that which is not written down or coded, often obtained through deep processing of information. Therefore, it has greater value and is particularly difficult to transfer [64].

Medical knowledge, like most other fields of knowledge, can be divided into two types: tacit and explicit [49, 69]. Explicit medical knowledge is written or codified as "fact," "scientific evidence," and other official documents generated by research and policy, such as clinical guidelines [58]. In contrast, tacit knowledge is generally less concrete, deeply rooted in practice, and is comprised of skills, ideas, and experience. This knowledge is more difficult to transfer than explicit knowledge [16]. Previous studies suggest that both explicit and tacit knowledge are important [49], however personal experiences appear to play a greater role in healthcare settings where the expertise of healthcare professionals is usually dominated by practice experience [22, 58]. Subsequently, tacit knowledge should receive more attention.

Existing research on explicit and tacit medical knowledge has mainly focused on distinguishing between explicit and tacit knowledge in healthcare settings [12, 17, 61], and on exploring the role played by these two types of knowledge [18, 24, 31, 58]. Such studies highlight the importance of tacit knowledge in delivering traditional medical care, but it is unclear whether tacit knowledge can still be useful in online contexts, as it is difficult to materialize. Therefore, it is necessary to explore the explicit and tacit knowledge generated in online medical environments, such as in OHCs.

2.2 Medical knowledge transfer in OHCs

Knowledge transfer is the process of sharing or disseminating knowledge between two or more parties through a medium [39]. Extant research classifies this knowledge transfer into explicit and tacit knowledge transfer and validates it on a variety of information system media [36]. Nonaka and Takeuchi [46] explained how explicit and tacit knowledge can be transferred from experts to novices in groups and organizations, which has been widely explored in online CoPs [4, 40]. Online communities are viewed as virtual platforms where knowledge transfer takes place. Faraj et al. [15] distinguished the flows of tacit and explicit knowledge in online communities and suggested that it can give rise to tacit knowledge transfer between participants. Previous studies demonstrate that online communities can effectively enhance and support the different phases of the knowledge transfer model [5].

As healthcare is a knowledge-intensive industry, it is crucial to establish a knowledge-exchange platform through which healthcare professionals can share, acquire, and use medical knowledge [2]. The emergence of OHCs has broken the limits of time and space, providing the possibility for knowledge transfer between remote physicians. In OHCs, the transfer of tacit knowledge is often in the form of discussions among physicians, which is aimed at exchanging ideas and experiences that are essential to one's ability to practice [64], while the transfer of explicit medical knowledge is often reflected in the sharing of clinical guidelines, relevant literature, and other materials by physicians, which are usually objectively accessible knowledge. The development of such knowledge platforms has, to some extent, enhanced the transfer of medical knowledge, especially tacit knowledge, among physicians [13, 47, 62].

Existing studies have explored the antecedents and consequences of knowledge transfer. Antecedents can be divided into individual levels, knowledge levels, and organizational levels [23, 42]. Among them, the importance of individual-level factors has attracted greatest attention, including intrinsic and extrinsic factors [73], such as attitude towards innovation [71], experience [29], and social capital [74], etc. Research on consequences has predominantly focused on innovative behavior [18] and service quality [53], etc., while few studies have discussed the impact of knowledge transfer from a cross-regional perspective. Goh et al. [19] found that knowledge flows in OHCs can reduce health gaps by developing the health capability of rural patients. Similarly, Cao and Wang [7] applied OHCs to urban–rural health inequality to empirically examine whether knowledge transfer in OHCs reduces health disparities between different regions in mainland China and drew the same conclusion.

However, to date, a lack of empirical research exists on knowledge transfer between physicians, especially since physicians' expertise plays a crucial role in healthcare delivery [47]. Furthermore, although the role of certain information technologies in facilitating the transfer of explicit and tacit knowledge has been explored [6, 62], few empirical studies have examined the process of cross-regional transfer of the two types of knowledge with the effectiveness of OHCs between different healthcare resource areas. Therefore, this study aims to explore the process of knowledge transfer between physicians in OHCs and identify whether OHCs can achieve an effective transfer of both explicit and tacit knowledge between different regions.

3 Methodology

3.1 Data collection

Data were collected from the original posts and replies to posts submitted to the Cardiology community on Lilac Garden from January 2017 to May 2020. In total, data were obtained from 4716 registered physicians. Lilac Garden is one of the largest professional OHCs in the world and the largest online community for physicians in China. The platform aims to provide a professional online community for medical and healthcare practitioners. In 2018, the platform had more than 2 million registered physicians. Many diseases discussed in the department of Cardiology are chronic diseases. The reason for choosing chronic diseases is that patients with this type of disease generally require long-term treatment and physicians must, therefore, have a strong understanding of patients' diagnosis and treatment plans at each stage, which has higher requirements for their professional ability. The data collected were divided into two parts for analysis. The first part contained users' posts and replies in the Cardiology community, representing physicians' interactions. The second part comprised the personal information of the physicians' departments and community characteristics from users' profiles.

A Python-based program was used to download data and classify them by province. Based on the China Statistical Yearbook [43], published in 2020, the 31 provinces in mainland China were divided into two parts on a ratio of 3 to 1 based on the 75% rule [50]. One part included a higher number of practicing physicians per 1000 population and another with a lower number. In this study, we describe the two parts as sufficient for the first 75 percent and insufficient for the remaining 25 percent. Before analysis, all invalid data was removed, such as special community managers and physicians whose geographic location was outside of the 31 provinces (e.g., Taiwan and Hong Kong). We finally obtained data from 3997 physicians from sufficient regions and 719 from insufficient regions. Table 1 shows the distribution of data by province. Furthermore, prior research demonstrates that physicians from regions with a higher GDP generally have better medical expertise than those from regions with a lower GDP [37], which means that a physician from a developed region is likely to be more professional. Therefore, we examined the effect of GDP on physicians' knowledge transfer in OHCs, which is the same as health technical personnel based on gross regional product per capita [43]. The two parts were identified as developed regions and less developed regions (see Table 1, column 3), with 4021 and 695 physicians, respectively. In summary, this study aims to examine the characteristics of knowledge transfer between different regions under two division methods.

3.2 Research methods

A directed unweighted social network was developed using the interactive relationship between posters and repliers. According to existing research [7, 19], posts can be divided into two types: information sharing and help seeking. For information sharing, the posters are regarded as suppliers, while repliers act as recipients, which means a flow from A to B if A replies to B's post at least once. Conversely, for help seeking, posters ask questions and wait for respondents to answer, with the flow being reversed [7]. The dxy forum divides its posts into different categories, taking cardiovascular as an example, such as academic frontiers, case studies, Electrocardiography (ECG), etc. Based on the platform criteria, we obtained the post and reply information separately. We consider image diagnosis, case discussion, and clinical experience as clinical skills, while the academic frontiers section is classified separately, which is the reflection of the tacit and explicit knowledge transfer in the OHC. With regards clinical skills, physicians express their views on a case and provide their diagnoses and suggested treatments for others to use as reference. In this scenario, intense discussion occurs where each physician contributes their tacit knowledge related to their treatment experience; this includes the sharing of typical cases or questions

Table 1 Province distribution based on health technical personnel and GDP

Province	Health workforce resource	GDP per capita	Frequency	Percentage (%)
Beijing	4.92	164,220	153	3.24
Zhejiang	3.51	107,624	1044	22.14
Jiangsu	3.16	123,607	276	5.85
Shandong	3.13	70,653	330	7.00
Shanghai	3.08	157,279	255	5.41
Inner Mongolia	3.08	67,852	43	0.91
Hebei	3.01	46,348	192	4.07
Ningxia	2.99	54,217	14	0.30
Tianjin	2.97	90,371	71	1.51
Jilin	2.94	43,475	47	1.00
Qinghai	2.86	48,981	9	0.19
Liaoning	2.85	57,191	116	2.46
Shanxi	2.84	45,724	66	1.40
Shaanxi	2.80	66,649	102	2.16
Hunan	2.75	57,540	149	3.16
Xinjiang	2.69	54,280	45	0.95
Chongqing	2.67	75,828	115	2.44
Tibet	2.66	48,902	4	0.08
Sichuan	2.65	55,774	217	4.60
Henan	2.61	56,388	221	4.69
Hubei	2.59	77,387	183	3.88
Guangdong	2.53	94,172	331	7.02
Hainan	2.53	56,507	14	0.30
Fujian	2.50	107,139	83	1.76
Heilongjiang	2.49	36,183	88	1.87
Guizhou	2.48	46,433	55	1.17
Gansu	2.37	32,995	59	1.25
Yunnan	2.35	47,944	76	1.61
Guangxi	2.32	42,964	112	2.37
Anhui	2.17	58,496	151	3.20
Jiangxi	2.07	53,164	95	2.01

about a difficult-to-treat disease. In the medical information part, most physicians ask for help or share some textbooks, images or videos, medical knowledge, cutting-edge research results, etc. Medical information offers a summary of existing literature, which is explicit knowledge and easier to obtain. However, clinical skills are considered physicians' personal experiences and directly manifest physicians' professional abilities, which belong to tacit knowledge, and are more difficult to transfer. Figures 1 and 2 provide two examples of these scenarios. The division of the sample by post type revealed that 2393 physicians were involved in tacit knowledge transfer and 736 physicians were involved in explicit knowledge transfer.

Finally, an overall network and two subnets were created. Each node in the network represents a physician, while the arrows represent an information flow via a directed dyadic tie. Prior studies have proven that a binary graph does not influence the interpretation of the information flow because it focuses on the region effect [1]. The summary statistics for various indicators of centrality for information support networks are provided in Table 2.

3.3 Exponential random graph models

Exponential random graph models were used to analyze the created network. ERGMs are a stochastic network modeling method based on exponential-family theory for analyzing the probability distribution of a set of networks [55]. This study aimed to explain how and why connections occur in the network; its explained variable is the probability of a network appearing. In fact, any network is a special case of the possible concentration of all the networks formed by the network nodes. This method seeks to analyze the special structural effects commonly

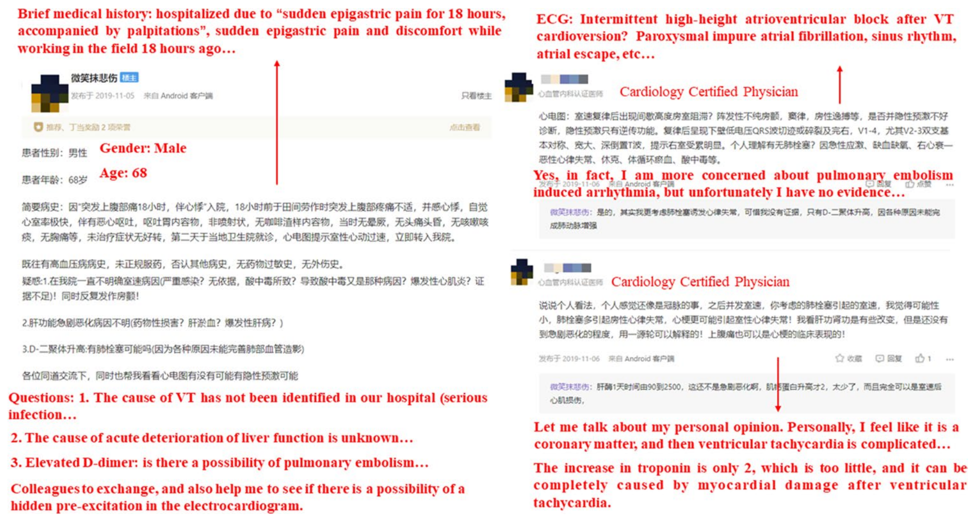

Fig. 1 Transfer of Clinical skills

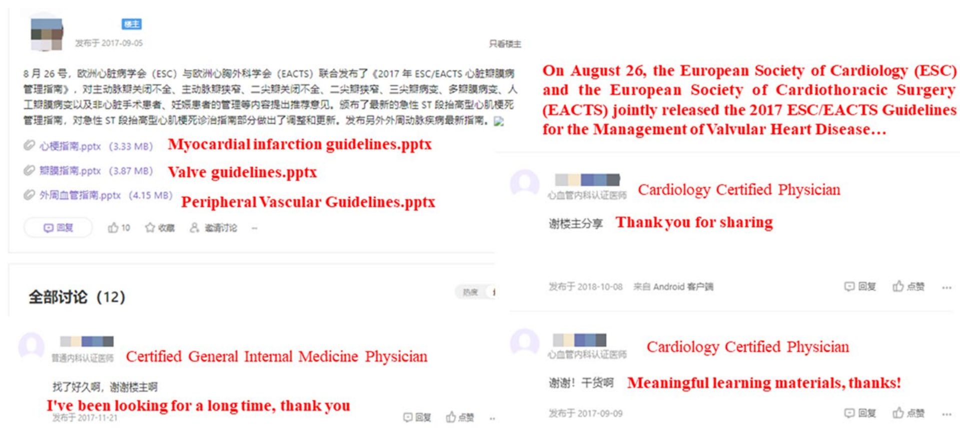

Fig. 2 Transfer of Medical information

observed in social networks, including reciprocity, transitivity, homophily, and attribute-based activity [54]. In this study, the mechanisms of reciprocity and individual-level attributes are tested interdependent of each other, where ERGMs are considered an appropriate approach for estimating how those mechanisms predict a network's ties formation [20]. The model is specified as follows:

$$\Pr(Y = y|\theta) = P_\theta(y) = \frac{1}{k(\theta)} \exp\left\{\theta^T z(y) + \theta_\alpha^T z_\alpha(y, x) + \theta_\beta^T z_\beta(y, g)\right\}$$

where $z(y)$ represents a set of network structure statistics that may influence the formation of relationships and organization in the network, $z_\alpha(y, x)$ is some network statistics about node attributes, $z_\beta(y, g)$ is a series of statistics related to other external relationship networks, and accordingly, $\theta, \theta_\alpha, \theta_\beta$ are the estimated parameter vectors of the corresponding network statistics. If these parameter estimates pass the significance test, then it indicates that the structure has an important influence on the formation of network relationships and organization construction. The positive estimated value of this parameter indicates that the structure in the network is higher than the randomly expected value when other conditions are controlled. Finally, $k(\theta)$ is a normalizing constant that ensures that the sum of probability equals one.

ERGMs were used for two main reasons. First, they allow dependent ties in the network, while most traditional network modeling approaches assume that network ties are independent [38]. This relaxed assumption is closer to the true network. Second, ERGMs use a bottom-up approach to model social networks, which is in line with the self-organizing nature of OHCs. The most common example of self-organizing network property is reciprocity [26], which is the structure of interest in this study. Robins et al. [55] found that ERGMs tend to produce more conservative estimates results than regressions.

3.4 Measures

This study examines the variables of network self-organization and actor attributes. Actor attributes include *department*, *reputation reward* (i.e., number of followers and likes), and *online rating*. Several variables were also incorporated

Table 2 Summary statistics for centrality of networks

Network type	Statistics	Obs	Mean	SD	Min	Max
Overall network	Degree centrality	4716	2.233	8.034	0	290
	Indegree	4716	1.117	4.888	0	169
	Sufficient indegree	3997	1.17	5.271	0	169
	Insufficient indegree	719	0.818	1.479	0	14
	Developed indegree	4021	1.141	5.204	0	169
	Less developed indegree	695	0.976	2.335	0	46
	Outdegree	4716	1.117	6.406	0	290
	Sufficient outdegree	3997	1.133	6.726	0	290
	Insufficient outdegree	719	1.025	4.207	0	95
	Developed outdegree	4021	1.123	6.615	0	290
	Less developed outdegree	695	1.081	5.035	0	95
Clinical skill network	Degree centrality	2393	2.342	5.689	1	122
	Indegree	2393	1.171	3.739	0	89
	Sufficient indegree	2044	1.189	3.965	0	89
	Insufficient indegree	349	1.063	1.948	0	14
	Developed indegree	2035	1.182	3.966	0	89
	Less developed indegree	358	1.109	2.014	0	15
	Outdegree	2393	1.171	4.346	0	122
	Sufficient outdegree	2044	1.183	4.569	0	122
	Insufficient outdegree	349	1.1	2.697	0	31
	Developed outdegree	2035	1.211	4.578	0	122
	Less developed outdegree	358	941	2.668	0	41
Medical information network	Degree centrality	736	1.587	2.771	1	50
	Indegree	736	0.793	1.366	0	24
	Sufficient indegree	636	0.803	1.43	0	24
	Insufficient indegree	100	0.73	0.851	0	5
	Developed indegree	635	0.792	1.389	0	24
	Less developed indegree	101	0.802	1.217	0	9
	Outdegree	736	0.793	2.615	0	50
	Sufficient outdegree	636	0.841	2.798	0	50
	Insufficient outdegree	100	0.49	0.643	0	3
	Developed outdegree	635	0.824	2.786	0	50
	Less developed outdegree	101	0.604	0.991	0	8

to control other factors that may influence the knowledge flows between regions (i.e., the number of posts and community points, which reflects users' activity). The definitions and interpretation of the variables are discussed below. Table 3 shows the descriptive statistics. Table 4 provides the configurations and network statistic definitions. The statnet package in R was used to estimate the built ERGM [21].

3.4.1 Network self-organization and actor attributes

The characteristics of individuals in the network is paramount to the formation of network connections [30, 48]. In considering OHCs, attributes of the community level are critical. In this study, *reputation reward* (i.e., number of followers and likes) was included to reflect how popular someone is in the OHC and *online rating* was used to reflect status capital. Physicians' *department* was added to reflect the variability of expertise among physicians in the OHC. Moreover, *activity* (i.e., post and point) was included for control purposes. In processing these attributes, we controlled for homophily, which suggests that two nodes with the same property form a connection.

3.4.2 Location measures

This study focused on the impact of geographical location (i.e., sufficient and insufficient, developed and less developed) on the features of knowledge networks, with the direct connections between the two kinds of regions being tested. Taking health technical personnel, as an example, they are divided into four types: sufficient→sufficient, sufficient→insufficient, insufficient→sufficient, and

Table 3 Description of variables

Variables	Description	Overall network				Clinical skills network				Medical information network			
		Mean	S.D	Min	Max	Mean	S.D	Min	Max	Mean	S.D	Min	Max
Reputation reward													
Followers	Number of physician followers	338.9	5806.0	0	334,000	447.8	7530.0	0	334,000	1190	13,919.2	0	334,000
Likes	Number of likes received by other physicians	425.9	2215.0	0	44,000	460.9	2517.9	0	44,000	658.1	3122.9	0	36,000
Status capital													
Online rating	Physicians' community level in the OHC	1.087	0.655	1	8	1.1	0.704	1	8	1.143	0.801	1	8
Variability of expertise													
Department	Department(s) where the physicians are employed	25.04	16.696	1	46	23.06	17.5	1	46	24.89	17.5	1	46
Community activity													
Post	Number of posts by physicians in OHCs	20.26	329.3	0	20,000	13.95	104.6	0	4415	52.08	750.1	0	20,000
Point	Number of points physicians have in OHCs	9.403	54.8	−20	1737	11.65	67.7	-5	1737	14.58	54.7	-20	552
Location													
Workforce resources	1: Physician in a sufficient region												
	0: Physician in an insufficient region	0.848	0.360	0	1	0.854	0.353	0	1	0.864	0.343	0	1
Economic resources	1: Physician in a developed region	0.853	0.355	0	1	0.850	0.357	0	1	0.863	0.344	0	1
	0: Physician in a less developed region												

Table 4 Network variables

Network statistic	Configuration		Definition
Edge	Edges	●→●	A benchmark possibility for tie formation of one node to another
Mutual	Reciprocity	●↔●	A possibility of connection from node *i* to *j* when the link, node *j* to *i*, exists. It is a measurement of reciprocity in the network
Homophily	Absdiff (follower)	○→○	Absdiff (follower) captures the tendency of tie formation between nodes due to the difference of the number of followers
	Absdiff (like)		Absdiff (like) captures the tendency of tie formation between nodes due to the difference of the number of likes
	Absdiff (post)		Absdiff (post) captures the tendency of tie formation between nodes due to the difference of the number of posts
	Absdiff (point)		Absdiff (point) captures the tendency of tie formation between nodes due to the difference of the number of points
	Nodematch (department)		Nodematch (department) means the possibility of the link, node *i* to *j*, when *i* and *j* are in the same departments
	Nodematch (level)		Nodematch (level) means the possibility of the link, node *i* to *j*, when *i* and *j* are in the same level in the community
Health technical personnel	sufficient→sufficient	●→●	A possibility of connection from node *i* to *j*, when both nodes *i* and *j* are from sufficient health technical personnel regions. This measure is to estimate the trend that a sufficient node points to a sufficient one
	sufficient→insufficient	●→○	A possibility of connection from node *i* to *j*, when node *i* is from sufficient health technical personnel regions and node *j* is from insufficient regions. This measure is to estimate the trend that a sufficient node points to an insufficient one
	insufficient→sufficient	○→●	A possibility of connection from node *i* to *j*, when node *i* is from insufficient health technical personnel regions and node *j* is from sufficient regions. This measure is to estimate the trend that an insufficient node points to a sufficient one
	insufficient→insufficient	○→○	A possibility of connection from node *i* to *j*, when both nodes *i* and *j* are from insufficient health technical personnel regions. This measure is to estimate the trend that an insufficient node points to an insufficient one
GDP	developed→developed	●→●	Similar to sufficient→sufficient. This measure is to estimate the trend that a developed node points to a developed one
	developed→less developed	●→○	Similar to sufficient→insufficient. This measure is to estimate the trend that a developed node points to a less developed one
	less developed→developed	○→●	Similar to insufficient→sufficient. This measure is to estimate the trend that a less developed node points to a developed one
	Less developed→less developed	○→○	Similar to insufficient→insufficient. This measure is to estimate the trend that a less developed node points to a less developed one

insufficient→insufficient. To avoid multicollinearity [19], sufficient→insufficient, and insufficient→sufficient, were respectively considered as a base group in the two models. On this basis, we calculated the value of the remaining three variables. The GDP group is approached in the same way.

4 Results

4.1 ERGM model results

The results of the overall network are shown in Table 5. Model 1 is a baseline model with two terms of edges and mutual. The first term indicates a baseline tendency of a node forming a tie with another, while mutual is about the reciprocity of two nodes in the network. A negative effect for edge suggests that the network density is lower than others that accidentally occur [75], while a positive coefficient for mutual implies that the relations for reciprocity of two nodes are more likely to appear in this network.

The other models include node attributes, location variables, and other control variables. First, with regard to location variables, Models 3 and 4 are used to analyze the directed knowledge flow between sufficient and insufficient regions. To better illustrate the possibility of the occurrence among different knowledge flows, we set *sufficient→insufficient* as a control group in Model 3, and *insufficient→sufficient* in Model 4. Our results show that *insufficient→sufficient* is

Table 5 Overall network estimation results of ERGM

Variable	Model1	Model2	Model3	Model4	Model5	Model6
Edge	− 8.328 < 1e−04***	− 7.595 < 1e−04***	− 7.342 < 1e−04***	− 7.482 < 1e−04***	− 7.494 < 1e−04***	− 7.553 < 1e−04***
Mutual	1.588 0.008**	1.247 < 1e−04***	1.262 < 1e−04***	1.246 < 1e−04***	1.292 < 1e−04***	1.281 < 1e−04***
Absdiff (post)		1.669e−04 < 1e−04***	1.687e−04 < 1e−04***	1.681e−04 < 1e−04***	1.671e−04 < 1e−04***	1.652e−04 < 1e−04***
Absdiff (point)		− 1.863e−03 < 1e−04***	− 1.900e−03 < 1e−04***	− 1.890e−03 < 1e−04***	− 1.859e−03 < 1e−04***	− 1.852e−03 < 1e−04***
Absdiff (follower)		6.107e−07 0.588	2.015e−07 0.853	1.550e−07 0.886	6.891e−07 0.526	6.552e−07 0.553
Absdiff (like)		4.317e−05 < 1e−04***	4.418e−05 < 1e−04***	4.406e−05 < 1e−04***	4.330e−05 < 1e−04***	4.327e−05 < 1e−04***
Nodematch (department)		0.144 < 1e−04***	0.149 < 1e−04***	0.149 < 1e−04***	0.147 < 1e−04***	0.147 < 1e−04***
Nodematch (level)		− 0.840 < 1e−04***	− 0.865 < 1e−04***	− 0.863 < 1e−04***	− 0.841 < 1e−04***	− 0.844 < 1e−04***
sufficient→sufficient			− 0.306 < 1e−04***	− 0.169 < 1e−04***		
insufficient→sufficient			− 0.136 < 1e−04***			
sufficient→insufficient				0.137 < 1e−04***		
insufficient→insufficient			0.044 < 1e−04***	0.181 < 1e−04***		
developed→developed					− 0.128 < 1e−04***	− 0.066 < 1e−04***
less developed→developed					− 0.061 < 1e−04***	
developed→less developed						0.062 < 1e−04***
less developed→less developed					− 0.052 < 1e−04***	0.010 < 1e−04***
AIC	98,229	97,554	97,482	97,482	97,550	97,549
BIC	98,259	97,674	97,646	97,646	97,713	97,713
Number of physicians	4716	4716	4716	4716	4716	4716

*$p \le 0.1$

**$p \le 0.05$

***$p \le 0.001$

negative in Model 3, while *sufficient→insufficient* is positive in Model 4, and they are all significant. This finding suggests that the *sufficient→insufficient* tie has a greater probability of existence, while insufficient→sufficient has a lower probability. By combining the results of the two models, the likelihood of physicians from sufficient regions replying to physicians from insufficient regions is higher than the likelihood of physicians from insufficient regions replying to ones from sufficient regions. As for Models 5 and 6, they examine the knowledge flow among developed and less developed regions. The negative and significant coefficient for *less developed→developed* implies that the flow from less developed regions to developed ones is less likely to occur in the network than from developed to less developed regions. A positive and significant value of *developed→less developed* shows that, in comparison with the flow from less developed to developed regions, the possibility of this occurring in the community network is higher. Existing studies prove the role of online health platforms in knowledge transfer from the patient perspective only [7, 19], and the results of this study validate it again from the physician perspective.

Secondly, node attributes were examined with results remaining consistent across all models, which shows that apart from the number of followers, other variables are all significant.

(1) *Reputation reward* There is no evidence that the number of followers of physicians influences the tendency for ties to form. However, a positive and significant coefficient for *Absdiff (like)* indicates that the greater the difference in the numbers of likes in OHCs between the nodes, the higher the possibility for a tie between them. *Like* can be regarded as the online reputation of physicians in OHCs, which represents how well they are recognized by others. Someone who receives more likes will possibly act as a knowledge supplier to maintain their reputation [41, 69]; therefore, knowledge transferred between physicians possessing varying amounts of likes is more likely.
(2) *Physicians' professional departments* The coefficient is positive and significant, which suggests that physicians in the same department are more likely to form ties (n.b., the same department refers to similar diseases, work, diagnosis, and treatment experience). Due to the higher clinical professionalism of physicians in the same department, more interactions occur [27].
(3) *Status capital* The negative coefficient of *Nodematch (level)* suggests that physicians with different online ratings are connected in OHCs. This finding is consistent with other studies on social groups and online communities where tenure is often shown to play an important part in predicting individual contribution behavior [3, 32]. Goh et al. [19], however, found that small differences in tenure, such as online ratings, created more supportive ties between patients. The reason for this may be that physicians belong to a highly specialized group, compared to patients. A physician with a higher rating has greater credibility and some young doctors turn to their senior counterparts for advice due to their limited professional experience, while the communication between physicians at the same level is relatively small.

Lastly, from the results of the control variables, we were able to draw an interesting finding. The nodes with the greater difference in the number of posts are more likely to generate connections, while the smaller the difference in the points, the easier it is to form a tie; this shows that users with more posts generally act as senders in the community and tend to pass on knowledge, while users with fewer posts tend to be recipients and absorb more knowledge from others. *Point* is another measure of a user's activity in the community. In general, the more points, the more active the user is in the community, and most of the knowledge transfer and reception in the community occur between active users, not the lurkers.

Table 6 shows the results of the knowledge subnets. The two types of knowledge results are described as follows. First, concerning location variables, the results of the clinical skills net show that the knowledge flow from developed to less developed regions is more likely to appear, compared to less developed→developed regions. However, the flow of sufficient→insufficient is not supported, while the knowledge flow of medical information net is supported in both classification methods. One possible reason for this is that physicians often work on cases that are described by someone and they combine this with their tacit knowledge (i.e., clinical experience) to provide a diagnosis and treatment plan in the clinical skill network. To transfer tacit knowledge in this network, physicians' professional ability must be strong, and, for medical information, physicians' explicit knowledge integration ability is more tested. Therefore, the regions' variable GDP, representing the quality of physicians, plays a significant role, while the variable, healthcare workforces, which represents the quantity of physicians, is not supported in the clinical skills net. In the medical information net, the professionalism of physicians in the process of explicit knowledge transfer is relatively low, so it is also supported in the type of regional divisions by the quantity of physicians.

Secondly, the results of node attribute of the two subnets with the overall net were compared. Our findings are as follows.

(1) *Reputation reward* The effect of *Absdiff (like)* in the two subnets is the same as the overall net. However, *Absdiff (follower)* is positive and significant in the medical information net. Similar to *likes*, the variable of *followers* is a reflection of physicians' reputation in OHCs and its role is supported in the subnet of medical information.
(2) *Physicians' professional departments* In the subnets, knowledge transfer is more likely to occur between physicians in the same department, which is consistent with the overall network finding.
(3) *Status capital* About the knowledge flows at different levels, the results of the clinical skill net are the same as the overall net. However, the medical information net is the opposite. A possible reason for this is that the online rating of the community also reflects, to some extent, the social status of physicians. In general, physicians with high community rankings are required to share their knowledge with others. Physicians who communicate clinical skills are often cross-hierarchical, as the disease discussion is often extremely specialized, with some high-level physicians generally providing tacit knowledge to other physicians. Conversely, medical knowledge is considered explicit knowledge (i.e., disease guidelines, literature, etc.) and the transfer of this knowledge usually occurs between low-level physicians.

Table 6 Subnets estimation results of ERGM

Variable	Clinical skills				Medical information			
	Model7	Model8	Model9	Model10	Model11	Model12	Model13	Model14
Edge	−7.601 < 1e−04***	−7.561 < 1e−04***	−7.525 < 1e−04***	−7.713 < 1e−04***	−7.687 < 1e−04***	−8.115 < 1e−04***	−7.641 < 1e−04***	−7.972 < 1e−04***
Mutual	0.120 < 1e−04***	0.059 0.024**	0.022 0.444	0.092 0.002**				
Absdiff (post)	−2.869e−04 0.002**	−2.898e−04 0.001***	−2.910e−04 0.001***	−2.982e−04 0.001***	7.040e−05 0.001***	7.040e−05 0.001***	6.977e−05 0.001***	6.977e−05 0.001***
Absdiff (point)	−9.211e−04 < 1e−04***	−9.462e−04 < 1e−04***	−9.674e−04 < 1e−04***	−9.487e−04 < 1e−04***	−3.467e−04 0.565	−3.467e−04 0.565	−3.094e−04 0.607	−3.094e−04 0.607
Absdiff (follower)	1.580e−06 0.130	1.571e−06 0.134	1.364e−06 0.185	1.404e−06 0.156	6.470e−06 < 1e−04***	6.470e−06 < 1e−04***	5.765e−06 < 1e−04***	5.765e−06 < 1e−04***
Absdiff (like)	6.348e−05 < 1e−04***	6.416e−05 < 1e−04***	6.458e−05 < 1e−04***	6.430e−05 < 1e−04***	8.731e−05 < 1e−04***	8.731e−05 < 1e−04***	8.988e−05 < 1e−04***	8.988e−05 < 1e−04***
Nodematch (department)	0.568 < 1e−04***	0.567 < 1e−04***	0.566 < 1e−04***	0.562 < 1e−04***	0.422 0.001***	0.422 0.001***	0.429 0.001***	0.429 0.001***
Nodematch (level)	−0.255 < 1e−04***	−0.255 < 1e−04***	−0.255 < 1e−04***	−0.254 < 1e−04***	0.608 < 1e−04***	0.608 < 1e−04***	0.638 < 1e−04***	0.638 < 1e−04***
Sufficient→sufficient	0.103 < 1e−04***	0.063 < 1e−04***			0.059 0.659	0.487 0.002**		
Insufficient→sufficient	0.041 < 1e−04***				−0.429 0.025**			
Sufficient→insufficient		−0.039 < 1e−04***				0.429 0.025**		
Insufficient→insufficient	0.016 < 1e−04***	−0.015 0.0001***			−0.982 0.056*	−0.554 0.289		
Developed→developed			0.043 < 1e−04***	0.230 < 1e−04***			−0.066 0.608	0.266 0.073*
Less developed→developed			−0.186 < 1e−04***				−0.332 0.071*	
Developed→less developed				0.186 < 1e−04***				0.332 0.071*
Less developed→less developed			−0.223 < 1e−04***	−0.032 < 1e−04***			−0.026 0.940	0.306 0.377
AIC	47,902	47,902	47,888	47,888	8791	8791	8802	8802
BIC	48,051	48,051	48,037	48,037	8903	8903	8914	8914
Number of physicians	2393	2393	2393	2393	736	736	736	736

*$p \leq 0.1$

**$p \leq 0.05$

***$p \leq 0.001$

Interestingly, we find that reciprocal relationships do not occur in the medical information network, whose coefficient is negative infinity. There are, however, differences between medical information and clinical skills. The former is more explicit, while the latter is more tacit, which requires more rich media exchange. Therefore, after an interaction occurs, the two physicians who exchange clinical skills usually form an invisible connection, which encourages them to continue communication and help each other when encountering similar problems in the future. General medical information acts as temporary support, only provided to physicians who need the knowledge urgently, and usually without further communication.

4.2 Robustness check

First, we tested the robustness of the results by randomly reducing the samples. The variables were retested by randomly reducing the number of physicians, 50 samples at a time. Moreover, to identify if the findings were sensitive to special network structures [19], such as physician community status, we performed ERGM by eliminating users who had the top likes (the top 10, 15, and 20). Third, to avoid the influence of two types of threads called an exogenous contextual factor, we tested these posts separately. Fourth, we found that physicians in Zhejiang province accounted for a large proportion of the network, so we replicated our analysis after excluding physicians from Zhejiang to check whether the results were purely driven by physicians from Zhejiang [26]. Additionally, in considering the difference between the two kinds of region physician sizes, which may influence our conclusions, we readjusted the regional division method to ensure that the two types of regions have a similar number of physicians (i.e., 50.42%, 51.86%, 52.72% in sufficient regions and 60.24%, 59.84%, 62.64% in developed regions, respectively in the overall net, clinical skills, and medical information net) for further test results. The results are presented in Table 7.

From our findings, it is suggested that physicians in insufficient and less developed regions receive a net surplus in every network built. It is, therefore, concluded that the study's findings are not sensitive to the number of physicians and the special characteristics. However, for the type of thread, the results seem to be partly unstable.

5 Discussion and implications

5.1 Discussion

This study used ERGMs to analyze the effect of variables, including network self-organization, control variables, and node attributions, on physicians' community network formation on OHCs. The study's results demonstrate that physicians with different reputation rewards (e.g., number of likes), status capital (i.e., community level), and who work in the same department, are more likely to transfer knowledge in OHCs.

Moreover, we examined the total effect of the quantity and quality distribution of physicians and the results are all supportive. The number of certified physicians per thousand population was used to measure the regional differences in quantity distribution. Physicians from sufficient regions were found to be more likely to provide online support to those working in insufficient regions. Meanwhile, developed regions seem to have more professional physicians [37] and, therefore, we separate the different regions based on GDP to explore the effect of the OHCs. The study's results show that physicians from developed regions are net suppliers of online information support to others from less developed regions. RQ1 is, therefore, answered and the OHCs do support the transfer of medical information between physicians across regions in China, especially since there is a significant flow of information from developed/sufficient to less developed/insufficient regions.

We subdivided the overall network into explicit and tacit knowledge subnets to answer RQ2. The study's results demonstrate that reciprocal relationships do not appear to exist in medical information networks, but do in clinical skills networks, suggesting that tacit knowledge transfer requires more continuous discussion among physicians and is more difficult to transfer, while explicit knowledge transfer is easier. Furthermore, our results show that connections appear between physicians with the same status capital in the medical information net, which indicates that explicit medical knowledge flows within one level and it is a cross-level flow in the tacit knowledge net. These results demonstrate that OHCs differ in transferring explicit versus tacit knowledge from a micro level and that these differences arise from the characteristics of the knowledge itself.

In the explicit network, our results are the same as the overall net. Since professional ability is demonstrated more in the transfer of tacit knowledge, physicians from developed regions are more likely to transfer tacit knowledge to others in less developed regions, and the flow from sufficient to insufficient is not proven. This result answers RQ1 at a fine-grained level while answering RQ2 for the differences in cross-regional transfer between the two types of knowledge. OHCs enable the cross-regional transfer of tacit knowledge on the GDP dimension, while the transfer of explicit knowledge exists in both the GDP and human resource dimensions. It also reveals the differences in cross-regional transfer between the two knowledge types from a macro perspective.

5.2 Theoretical implications

This study explores the effectiveness of OHCs in allowing physicians to transfer knowledge, especially tacit and explicit knowledge, and examines the knowledge flows from sufficient to insufficient and developed to less developed regions. The findings reveal the differences between tacit and explicit medical knowledge flows and, hence, this study offers several theoretical implications.

First, this study provides evidence showing which physicians transfer knowledge through OHCs and finds which scenarios this knowledge transfer primarily occurs in to extend our understanding of the social value created by physicians in OHCs. By discussing the interaction between physicians in different health resource allocation regions, overall knowledge flows are found to occur from areas of superior quantity and quality to areas of lesser superiority. OHCs are a type of digital platform where a high level of information asymmetry exists for both physicians and patients [70]. For example, highly skilled physicians from developed regions know more about medical dynamics or diagnosis and have greater treatment experience. Others can provide more suitable services based on the information found in OHCs to enhance their capability. To date, prior research has mainly focused on online patient communities to explore the direct impact of OHCs in reducing the gap through enhanced patient health capability [7, 19]. However, the role of physicians is often neglected. This study, therefore, focuses on the effect of online physician communities in improving the problem of health resource allocation via knowledge transfer, thus reducing health service disparities among regions. Moreover, we demonstrate the social value created by OHCs.

Table 7 Robustness of test results

Network types	Variable	− 50 physicians	− 100 physicians	− 150 physicians	Top 10 likes removed	Top 15 likes removed	Top 20 likes removed	information sharing	Help-seeking	Zhejiang removed	Regional average distribution (human resource and GDP)
Overall network	sufficient→ insufficient	0.297 < 1e−04***	0.372 < 1e−04***	0.267 < 1e−04***	0.148 < 1e− 04***	0.505 < 1e− 04***	0.350 < 1e−04***	− 0.632 < 1e−04***	− 0.255 < 1e−04***	0.020 < 1e−04***	0.045 < 1e−04***
	insufficient→ sufficient	− 0.298 < 1e−04***	− 0.372 < 1e−04***	− 0.261 < 1e−04***	− 0.147 < 1e−04***	− 0.506 < 1e−04***	− 0.352 < 1e−04***	0.634 < 1e−04***	0.254 < 1e−04***	− 0.020 < 1e−04***	− 0.046 < 1e−04***
	developed→ less developed	0.373 < 1e−04***	0.109 < 1e−04***	0.203 0.0004***	0.025 < 1e−04***	0.360 < 1e−04***	0.328 < 1e−04***	− 0.382 < 1e−04***	0.205 < 1e−04***	0.278 < 1e−04***	− 0.149 < 1e−04***
	less developed→ developed	− 0.371 < 1e−04***	− 0.109 < 1e−04***	− 0.197 0.001***	− 0.021 < 1e−04***	− 0.360 < 1e−04***	− 0.330 < 1e−04***	0.386 < 1e−04***	− 0.205 < 1e−04***	− 0.278 < 1e−04***	0.148 < 1e−04***
Clinical network	developed→ less developed	0.283 < 1e−04***	0.164 < 1e−04***	0.261 < 1e−04***	0.181 < 1e−04***	0.190 < 1e−04***	0.180 < 1e−04***	0.806 < 1e−04***	0.154 < 1e−04***	0.593 < 1e−04***	0.246 < 1e−04***
	less developed→ developed	− 0.277 < 1e−04***	− 0.166 < 1e−04***	− 0.258 < 1e−04***	− 0.182 < 1e−04***	− 0.188 < 1e−04***0	− 0.185 < 1e−04***	− 0.802 < 1e−04***	− 0.157 < 1e−04***	− 0.595 < 1e−04***	− 0.248 < 1e−04***
Medical information	sufficient→ insufficient	0.115 < 1e−04***	0.423 < 1e−04***	0.522 < 1e−04***	0.394 < 1e−04***	0.139 < 1e−04***	0.146 < 1e−04***	1.594 < 1e−04***	− 0.371 < 1e−04***	0.516 < 1e−04***	0.199 < 1e−04***
	insufficient→ sufficient	− 0.112 < 1e−04***	− 0.427 < 1e−04***	− 0.494 < 1e−04***	− 0.394 < 1e−04***	− 0.144 < 1e−04***	− 0.149 < 1e−04***	− 1.581 < 1e−04***	0.363 < 1e−04***	− 0.518 < 1e−04***	− 0.196 < 1e−04***
	developed→ less developed	0.235 < 1e−04***	0.332 < 1e−04***	0.335 < 1e−04***	0.329 < 1e−04***	0.172 < 1e−04***	0.165 < 1e−04***	0.758 < 1e−04***	0.049 < 1e−04***	0.330 < 1e−04***	0.279 < 1e−04***
	less developed→ developed	− 0.243 < 1e−04***	− 0.331 < 1e−04***	− 0.326 < 1e−04***	− 0.324 < 1e−04***	− 0.175 < 1e−04***	− 0.167 < 1e−04***	− 0.771 < 1e−04***	− 0.050 < 1e−04***	− 0.316 < 1e−04***	− 0.283 < 1e−04***

*$p \le 0.1$
**$p \le 0.05$
***$p \le 0.001$

Second, this study shows the networks of interactions between physicians in OHCs regarding explicit and tacit knowledge and discusses the characteristics of each of the two types of knowledge transfer networks to enrich the literature on physician online interactions. Although previous studies have identified the existence of explicit and tacit knowledge exchange in online CoPs, the characteristics of these two types of knowledge transfer networks have not been explored [8, 10, 44]. Moreover, OHCs, an important type of online community, have received less attention than other types of communities. Tacit and explicit knowledge play different roles in the medical field, with some studies suggesting that tacit medical knowledge is more important for physicians as it helps guide their practice [22, 58]. We found that due to the difficulty in transferring medical tacit knowledge, users usually form a hidden connection during discussions with others, and this connection makes them continue to help each other in the next discussion while, explicit knowledge, due to its multiple access channels and content that has been coded and processed several times, or confirmed, does not require additional discussions to achieve transmission. Additionally, unlike explicit knowledge, tacit knowledge is usually transferred across physician levels.

Third, this study demonstrates the cross-regional transfer characteristics of explicit and tacit knowledge to complement studies on the effectiveness of OHCs to transfer different types of knowledge. We found that the transfer of explicit knowledge among physicians can occur between regions with large differences in the quantity and quality of human resources, which may be related to the ease of access to explicit knowledge. In contrast, the amount of tacit knowledge reflects the professional competence of a particular physician, so the transfer of tacit knowledge is only significant between developed and less-developed regions, which is more indicative of the quality of human resources.

5.3 Practical implications

This study provides important practical implications to improve current understanding about how tacit and explicit knowledge transfer between physicians in networks are organized in the specific context of China and reveals the connections and relationships between the nodes in such a network. The study's results are relevant to developers and users of OHCs and should help in the future creation and deployment of OHCs.

First, the importance and value of OHCs are increasingly being appreciated by the research community. However, compared with patient-to-patient and physician–patient communities, the importance of physician-to-physician communities appears somewhat neglected. Healthcare policymakers should, therefore, pay greater attention to platforms that encourage physician communication as the benefits to physicians of online social networks have been proven. To address and improve the health inequities and narrow the gap between different regions, governments should strongly support the participation of not only patients but also physicians in OHCs; they must be introduced to them from the perspective of both physicians and patients. For example, governments can increase investment in online physician communities, while healthcare policymakers can create policies that encourage physicians to engage with them.

Second, tacit knowledge is extremely difficult to transfer as it requires continuous mutual discussion between physicians. Therefore, this study suggests that OHCs can introduce friend recommendations so that the invisible connection formed by physicians who have exchanged clinical experiences once can be visualized. This would allow them to hold further discussions when they encounter similar problems. In addition, with regards the transfer of explicit medical knowledge, OHCs can help users integrate knowledge so that physicians in need can more easily retrieve the information they require, ultimately enhancing the efficiency of knowledge transferred in OHCs.

Third, this study provides an auxiliary means for physicians, with relatively junior qualifications and poor ability, to learn clinical expertise, acquire practical experience and, thus, accumulate tacit medical knowledge, which is of vital importance to their clinical practice. Therefore, it is strongly recommended that physicians working in less developed regions who have relatively limited learning opportunities in the real environment attend the parts of case discussions or medical information in OHCs to obtain more chances to learn from others, especially experts in the field. Meanwhile, they can raise their problems in the community to find the most appropriate solutions and improve their service delivery.

5.4 Limitations and future research

This study has several limitations that can be addressed in future research. First, only physicians' online characteristics and those of their departments were considered, while other unobserved factors, such as physicians' titles, hospital level, etc. may have affected the level of knowledge transfer in OHCs. Second, the ERGM models reported in this study were created using a simple directional binary network. Although this can conservatively account for the physician relationship network, future studies should develop weighted networks or two-mode networks to provide more valuable insights. Third, the study's results seem to be unstable in the type of help-seeking network. This may be attributed to the subjectivity of manual classification. Future studies can use supervised machine learning methods to classify the content of posts found in OHCs. Finally, this study only included physicians who had posted or replied to posts in the OHC, but it is argued that any physician who browses the threads in OHCs are likely to benefit as a receiver, even though they do not post. Therefore, the evidence presented in this study should be considered as a conservative estimate, which reflects a subset of the knowledge transferred by physicians in OHCs.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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