Modelling of practice sharing in complex distributed healthcare system

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Abstract. This research investigates how collectives of doctors influence their diagnostic method preferences within small-world network social structures through participation in diverse types of medical practice-sharing activities across different scales. We propose an approach based on vectorization of the preferences for various diagnostic methods among physicians, quantifying their openness to these methods using the Shannon diversity index. Utilizing theoretical foundations from threshold models, influence models, and the Hegselmann-Krause model, we designed simulation experiments for teaching activities and seminars to explore the dynamic changes in preference vectors and Shannon diversity indices among these doctors in a small-world network. We evaluated our approach with a real-world data set on vertigo treatment by several clinical specialists of different specialty (neurologists, otolaryngologist). Building on real data from this initial group, we then simulated data for a large number of doctors from various medical communities to examine phenomena in larger-scale systems. Hierarchical networks featuring small-world properties were developed to simulate "local" within-community and "global" across-community seminars, reflecting different intra- and inter-community scenarios. The experiments show different patterns of practice converging during simulation in various scales and scenarios. The findings of this study provide significant insights for further research into practice-based knowledge sharing among healthcare professionals, highlighting the nuanced interplay between social network structures and professional consensus formation.

Keywords: community behavior, complex networks, practice sharing, complex systems, diagnostic method preferences, hierarchical network

1 Introduction

Recognizing that competencies are distributed within a healthcare setting (i.e., collective competence) is vital [1]. The healthcare sector is not only largely distributed and fragmented but it also exhibits a high degree of diversity with strong local autonomy [2, 3]. In the healthcare sector, various medical tasks face diverse, multi-level, large-scale,

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DOI: 10.1007/978-3-031-63772-8_21

and complex challenges that are intrinsically linked with the concept of "distributed" systems [4, 5].

Healthcare is usually considered as highly regulated systems with large number of norms such as clinical recommendations, protocols, internal and external hospital rules, etc. Still, due to high complexity of disease, multiple decisions are made by doctors in accordance to their experience or known “best practices” within certain degree of freedom under regulation. Here we consider "practice" as a significant pattern of clinical decision making. Such patterns are optimized and refined through continuous dynamic interaction, thereby facilitating the sharing and transfer of knowledge between different but related tasks [6]. In the healthcare domain, practice specifically includes diagnostic practice [7], emergency response practice [7], disease management practice [8], preventive medical practice [9], and rehabilitation practice [9]. Therefore, it is necessary to investigate the process of practice sharing within distributed healthcare environments with multiple doctors with different communication channels.

In medical practice, vertigo is a common symptom but poses diagnostic and treatment challenges due to its diverse etiologies and complex clinical presentations. When faced with patients exhibiting symptoms of vertigo, different doctors might make varying clinical decisions even in the face of similar cases. This variability partly stems from the lack of unified clinical guidelines and recommendations, and partly from each physician's preferences for clinical examination and diagnostic tests. Significant differences in the adoption rates of specific diagnostic tests by doctors have been observed, even for similar symptoms [10, 11]. Some doctors may prefer to use balance tests like the Romberg's test, while others might rely more on hearing tests, such as Weber's test. Furthermore, for the assessment of vertigo, some physicians might frequently use the Headshake test, while others might more commonly employ gait analysis tests and tests related to respiratory responses, such as the hypercapnic response.

Building upon this foundation, our research motivation is to deeply understand how groups of physicians influence and shape their diagnostic method preferences through the sharing of “practice” within distributed healthcare environments. Our research aims to identify the key factors influencing the formation of physicians' diagnostic method preferences and to understand how these preferences evolve in a distributed medical environment through patterns of practice sharing[12].

This study not only offers a new perspective for understanding the sharing of “practice” in medical decision-making but also provides a theoretical foundation for further exploration of practice-based knowledge sharing among healthcare professionals. Through this research, we aim to offer insights into the mechanisms of knowledge sharing and social interaction in medical decision-making and practice, especially in addressing diagnostic challenges. We seek to demonstrate how improving knowledge sharing and social interactions can enhance the quality and efficiency of medical services.

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2 Modelling practice sharing in complex healthcare system

Here, by “practice” in healthcare we consider patterns in clinical decision making which appears multiple times in treatment of similar patients. The most important role is played by practices in situation where official regulation (by clinical recommendations, protocols, etc.) give certain degree of freedom to a doctor, or in situations where there is no strict protocols (e.g. in appearance of new disease, or in complex diseases). In turn, "practice sharing" refers to the dissemination of medical knowledge and information related to practices within a distributed healthcare environment where good practices may be shared or recommended by experienced specialists (e.g. explicitly during dedicated meetings or implicitly during common information sharing).

Several studies have touched upon the concept of practice sharing. However, these investigations often did not formally define or scientifically model the concept, leaving room for more rigorous research and analysis in this area. Prasidh Chhabria et al. [6] and Kyunghoon Hur et al. [13] actually explored practice sharing between different healthcare tasks. Wei Gong et al. discussed the practice sharing of various smart intensive care units [14]. Corinna Maier et al. discussed the "practice sharing" of continuous precise drug dosage use across hospitals or research centers [15] .

We introduce a constructive modeling approach and process for the nascent field of distributed medical practice sharing. Our modeling approach studies physicians, hospitals, and different types of medical sharing events. The model structure is shown in Fig.1.

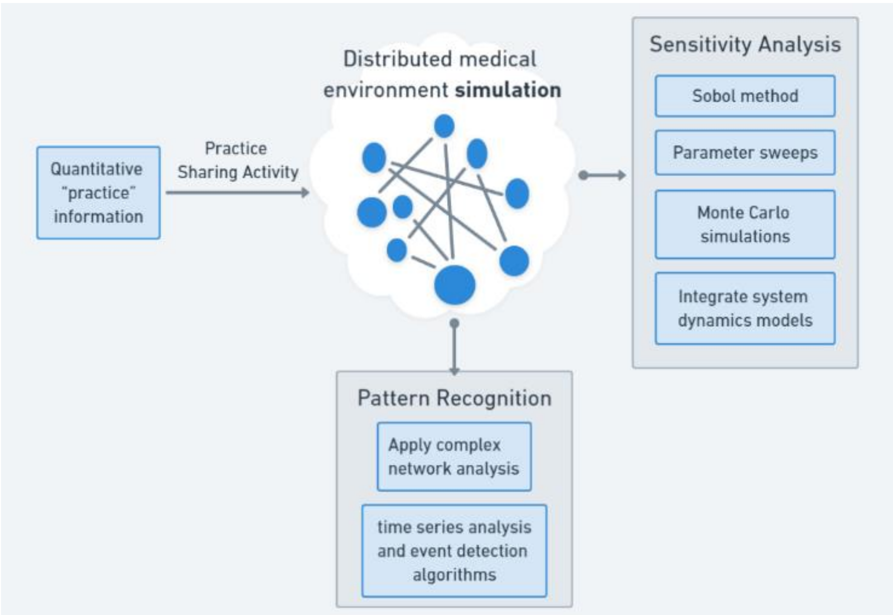

Fig. 1. General approach for modelling of practice sharing

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2.1 Quantitative Medical Practice

The content of medical data sets is diverse [2, 16], medical practice information exists in datasets in various implicit forms. We suggest mining this information from the perspective of medical practice preferences. Specifically, we use medical Practice Preference Vectors and Physician Shannon Diversity Index to measure medical practices.

Given a medical dataset D and a binary vector representation for each physician i based on X unique diagnostic items, the real Practice Preference Vector $\boldsymbol{P_i}$ for physician i is defined as a vector of proportions $[p_{i1}, p_{i2},\ldots, p_{ix}]$, where each element p_{ij} represents the proportion of times diagnostic item j was employed by physician i relative to their total usage of all X diagnostic items. This formulation refines the initial binary encoding to quantify the diagnostic preferences of physicians, capturing the relative frequency of each diagnostic item's use. Formally, P_i is obtained by:

$$\boldsymbol{P_i} = \left[\frac{n_{i1}}{N_i}, \frac{n_{i2}}{N_i}, \ldots, \frac{n_{iX}}{N_i}\right] \tag{1}$$

Where n_{ij} is the number of times physician i used diagnostic item j, N_i is the total number of diagnostic items used by physician i, X is the total number of unique diagnostic items in dataset D.

Physicians' practice preferences are typically formed based on long-term experience and are not prone to significant changes in the short term, making longitudinal analyses more relevant and meaningful. The preference for specific practices is distinct from the dynamics and adaptability of practices themselves. Short-term analyses or assessments at a specific point in time fail to capture meaningful patterns or trends in physicians' practice preferences. Therefore, we employ the Shannon diversity index for a macro-level quantification of physicians' overall preferences for different diagnostic methods over extended periods. This approach not only reflects the overall distribution of physicians' preferences but also effectively reveals the diversity and breadth of diagnostic practices on a larger scale. Such a macro-analytical method provides a valuable perspective for understanding physicians' diagnostic preferences, aligning well with the practical requirements of medical practice data analysis.The physician's Shannon diversity index H can be calculated using the following equation:

$$H = -\sum_{i=1}^{R} p_i \log(p_i) \tag{2}$$

Where, R is the total number of diagnostic methods, p_i is the probability of the i_{th} diagnostic method (i.e., the frequency of use of this method relative to the total number of uses).

2.2 Physician Practice Sharing Activity

In the actual medical environment, the sharing of practices in their implicit forms among physicians is realized through a variety of sharing activities with different types and natures. These activities are divided into two main categories: educational activities with a presenter and seminars among physicians. The preferences in practices among physicians may shift after participating in these different activities. Within our

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modeling approach, it is essential to simulate both categories of activities to explore how these practice-sharing endeavors in their implicit forms affect the quantified information on medical practices we have established. We provide original simulation algorithms based on different theoretical models.

Teaching activities. We employ a hybrid application of Influence Models [17] and Threshold Models [18] as the theoretical basis for the implementation of "teaching activities." Teaching activities are hosted in rotation by doctors, with the presenting doctor exerting an influence (ϕ) on their "direct neighbors" within the network structure. Due to the potential difference in magnitudes between a doctor's Shannon diversity index and the total usage of diagnoses by the doctor, we need to balance their impacts. We employ min-max normalization: converting the values of diagnostic usage to a range between 0 and 1. After normalization, we can calculate the weighted average. The influence is calculated using the Weighted Average Method, with the formula as follows:

$$\phi = w_s \times S_{speaker} + w_u \times U_{norm} \tag{3}$$

Where, ϕ represents the influence of the activity. $S_{speaker}$ is the Shannon diversity index of the speaker. U_{norm} is the normalized total usage of diagnoses. w_s and w_u are the weights assigned to the speaker's Shannon diversity index and the total usage of diagnoses, respectively.

After determining the influence (ϕ), we update the Shannon diversity index for direct neighbors of the speaker doctor, simulating knowledge exchange and adaptation dynamics. The update utilizes a linear adjustment, based on the relative Shannon diversity indices ($S_{speaker}$ and $S_{neighbor}$), encapsulating learning responses. The unified formula for both positive and negative adjustments is:

$$S'_{neighbor} = S_{neighbor} + \alpha \times \left(\text{sign}\left(S_{speaker} - S_{neighbor}\right)\right) \times \left|\phi - S_{neighbor}\right| \tag{4}$$

For preference vectors, the update is governed by a linear adjustment towards the presenting doctor's preferences, encapsulated as:

$$\boldsymbol{P}'_{\boldsymbol{n}} = \boldsymbol{P}_{\boldsymbol{n}} + \alpha \times (\boldsymbol{P}_{\boldsymbol{s}} - \boldsymbol{P}_{\boldsymbol{n}}) \tag{5}$$

Where $\boldsymbol{P}'_{\boldsymbol{n}}$ and $\boldsymbol{P}_{\boldsymbol{n}}$ represent the updated and current preference vectors of a neighbor doctor, respectively, $\boldsymbol{P}_{\boldsymbol{s}}$ is the preference vector of the presenting doctor, and α is the learning rate. This formula ensures that each neighbor's preferences incrementally align with those of the presenter, reflecting the adaptative learning process within professional networks.

Seminars for Practice sharing. Given the nature of seminars as spaces for professional dialogue and learning, the HK model [19] is particularly suitable for simulating these events. Based on the HK model, the Shannon index update algorithm is as follows.

$$S'_i = \frac{1}{|N_i| + 1} \times \left(S_i + \sum\nolimits_{j \in N_i, [S_j - S_i] \leq \tau} S_j\right) \tag{6}$$

Where, S'_i represents the updated Shannon diversity index of doctor i. S_i is the current Shannon diversity index of doctor i. N_i denotes the set of neighbors of doctor i whose Shannon indices differ from S_i by no more than a threshold τ (opinion acceptance threshold). $|N_i|$ is the count of such neighbors. τ is defined as the boundary of the confidence interval, wherein the influence between nodes is considered for adjustment only

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if the difference in their Shannon diversity indices falls within this range. This implies that an individual considers the opinions (or, by analogy, diagnostic practices) of their peers to be sufficiently credible or relevant only when the disparity in their Shannon diversity indices does not exceed τ.

Extending the Hegselmann-Krause model to preference vector updates in seminars involves calculating the updated preference vectors $\boldsymbol{P}_i'$ of doctors by averaging the preferences of neighbors within a specific Euclidean distance (δ), then adjusting towards this average with a strength (α). The core update formula simplifies to:

$$\boldsymbol{P}_i' = \alpha \times \left(\frac{\sum_{j \in N_i, d(\boldsymbol{P}_i, \boldsymbol{P}_j) \le \delta} p_j}{|N_i|}\right) + (1-\alpha) \times \boldsymbol{P}_i \tag{7}$$

$\boldsymbol{P}_i$ and $\boldsymbol{P}_i'$ are the current and updated preference vectors of doctor i, $d(\boldsymbol{P}_i, \boldsymbol{P}_j)$ is the Euclidean distance between the preferences of doctors i and j, δ is the distance threshold for considering neighbors' influences, N_i is the set of neighbors within δ of i, α controls the update intensity, blending the average neighbor preference with $i's$ current preference.

2.3 Distributed medical network structure.

The doctors in the hospital are a closely connected professional community for communication. Reflecting this real-world characteristic, we adopt the "small-world network" model to simulate the complex communication and influence propagation paths among doctors [20]. We construct the small-world network here using three key parameters: the number of doctors, the rewiring probability , and the mean degree (number of connections per node).

We consider each doctor as a node within the network, with nodes featuring three attributes: the doctor's name, practice preference vector, and Shannon diversity index. Edges represent the practice-sharing relationships among doctors. Not all doctors have actual sharing relations in reality. Thus, we simulate this aspect by adjusting the mean degree and the rewiring probability. For instance, a higher mean degree reflects close communication and cooperation relationships among doctors within a community. The rewiring probability models the opportunities for communication within the community, even among doctors who are geographically distant or have slightly different professional orientations.

To visually represent the Shannon diversity index of doctors, we utilize the color of the nodes in the network diagram, where the similarity in colors indicates the closeness of the Shannon diversity indexes.

2.4 Simulation

The purpose of the simulation experiment is to investigate the specific impacts of two types of sharing activities on the practices of physicians within hospitals, with a primary focus on two aspects.

1.Simulation Time. Depending on the experimental scenarios, datasets, and re-search objectives, it is necessary to set varying simulation durations to capture the dynamics

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of the system. This may include simulations based on multiple specific time points, long-term simulations, and repetitive cyclical simulations.

*2. Simulation Scale.*The size and complexity of the simulation must be tailored to accommodate the scope of the experimental framework and the granularity of the analysis desired. This involves determining the number of agents or entities, the extent of the networked environment, and the volume of data to be processed. Choices range from small-scale simulations focusing on detailed interactions within a confined setting, to large-scale simulations that aim to replicate broader system-wide dynamics across multiple interconnected scenarios.

2.5 Evaluation Analysis Methods

The final step in the model is the evaluation and analysis of data derived from the simulation experiments. The main methods can be divided into 2 categories.

1. Sensitivity Analysis: Implement global sensitivity analysis, such as the Sobol method, to quantitatively assess the impact of varying input parameters on simulation outcomes; Utilize parameter sweeps and Monte Carlo simulations to evaluate the robustness of the model against parameter variations and identify key parameters; Integrate system dynamics models to assess system behavior under parameter changes and use this information to optimize the model.

2. Pattern Recognition: Apply complex network analysis to identify collective behaviors and diffusion patterns in medical practice, such as using community detection algorithms to discover group structures within practice sharing;Employ time series analysis and event detection algorithms to track and recognize the temporal dynamics and trends of practice sharing.

3 Practice sharing in vertigo treatment

In this section, we conduct a study on diagnostic practice sharing using a dataset from a 2016-2020 vertigo clinic in Rostov-on-Don. This exemplifies our practice sharing research model, illustrating its application in studying how physician groups shape diagnostic preferences through small-world networked activities.

3.1 Data set and processes

Vertigo, particularly Benign Paroxysmal Positional Vertigo (BPPV), is a complex condition characterized by a multitude of etiologies and the involvement of various medical specialists, including neurologists and otolaryngologists, among others. The diagnosis and treatment of vertigo and BPPV involve a range of methods, from specific diagnostic tests to repositioning maneuvers, such as the Dix-Hallpike test and Epley maneuver, underscoring the multifaceted approach required to manage this condition effectively [21].

The original data is composed of 10 structured .xlsx files with 40 fixed headers.These headers have five main classes: patient basic information, diagnostic and

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treatment information, medical history and status records, treatment and recommendations, and patient background information. Our dataset's mixed-format data was processed to abstract "practice" information via tokenization, keyword extraction, and subsequent lemmatization, followed by categorization to compute proportions and formulate both practice information data and doctor preference vectors.

During pre-processing phase, we structure the practice information, which contains detailed medical diagnostic information aggregated by unique appointment card numbers. Each unique appointment card number represents an individual patient and is associated with 125 different diagnostic items. For each diagnostic item, the file meticulously records the specific di-agnostic outcomes, provided in text format.

We use the algorithm in Section 2.1 to obtain the preference vector of each doctor under the current data set. The table below, Table 1, describes the structure of the Doctor Preference Vectors.

Table 1. Structure of the Doctor Preference Vectors

Doctor Neurologist	Total usage	Romberg's test	Hallpike test	123 items remaining
Doctor A	538	0.3086	0.2472	***
Doctor B.	18024	0.1353	0.1263	***
Doctor C	585	0.4154	0.3487	***
Doctor D	1078	0.3878	0.2653	***
Omit 6 doctors' names	***	***	***	***

3.2 Model Identification, Validation, and Sensitivity Analysis Based on Actual Data

First Experiment and parameter sensitivity analysis Based on Actual Data. The first experiment was conducted based on additional information provided by the dataset creators. From this first experiment, we obtained parameters that fit the dataset information.

From 2016 to 2020, there were nine "teaching activity" events and eight "seminar" events conducted. During this period, from 2017 to 2020, each year featured two "teaching activities" and two "seminars," with 2016 hosting only one "teaching activity."

Initially, we assigned default values to the parameters in Formulas 2 to 6 for simulating 17 events within our model on actual timelines. We algorithmically extracted the real preference vectors of ten doctors before December 31st each year and evaluated their fit with the simulation by calculating the Euclidean distance to the actual vectors. Through parameter sweeps and Monte Carlo simulations, we fine-tuned the simulation to closely match the real data, setting rewiring_prob=0.3, mean_degree=4, α =0.05, w_s=0.5, w_u=0.5, τ =0.2, and δ =0.5 after iterative adjustments.

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With the given parameters, we measured yearly Euclidean distances between simulated and actual preference vectors for 10 doctors, summarizing with average, median, and range (max and min) to evaluate our model's accuracy, as Table 2 illustrates.

Table 2. Preference vector comparison results.

Year	Average Distance	Median Distance	Max Distance	Min Distance
2016	0.64	0.5	2	0
2017	1.21	1	2	0
2018	1.38	1.41	2	1
2019	0.88	1	2	0
2020	1.11	1	2.24	0

We compared two preference vectors, each composed of 125 binary values corresponding to 125 diagnostic items. The average value calculated in column 2 of Table 2 is 0.88, indicating that the annual difference between simulated and actual doctor preference vectors is less than one out of 125 items. In other words, the preference changes in the 125 simulated diagnostic items closely match those observed in the actual dataset.

3.3 Simulation Scenario Expansion: Long-term, Large-scale, and Variant Studies

In the experimental results based on the above parameters and actual time nodes, although the final preference vectors of the 10 doctors are consistent with the data in the data set, there was no consensus among the doctors at the end of 2020.

So based on parameters obtained from the first experiment, we extended the simulation period from January 1, 2016, to December 31, 2026. "Teaching activities" were scheduled monthly, while "seminars" occurred weekly.

By increasing the frequency of "practice sharing" events, we aimed to observe the system's dynamics over an extended simulation. The experiment revealed that after 117 months, the Shannon diversity indices of all ten doctors converged to a single value, resulting in identical preference vectors for each doctor (see Fig. 2). In Fig. 2, A to J represent the 10 doctors in the original data set.

Subsequently, leveraging information extracted from a real dataset comprising ten doctors, we employed methods such as non-uniform probability selection, random non-repetitive sampling, normalized random allocation, and an overarching simulation framework to generate preference vector files for 1000 doctors from ten different medical sharing communities.

We then refined the seminar model based on the Hegselmann-Krause (HK) model to simulate "local seminars" within communities and "global seminars" across communities. Different reconnection probabilities and average degrees were used to mimic the network structures within and between communities, constructing a hierarchical small-world network across ten communities. Higher average degrees and reconnection probabilities were used in intra-community networks, reflecting the higher frequency of

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interaction and closer collaboration among doctors within the same community (understood as the same hospital, city, or group of doctors with similar professional backgrounds). For inter-community network configurations, lower average degrees were adopted to represent the greater challenges and fewer direct contacts in interactions between doctors from different communities (or different specialties and geographical locations).

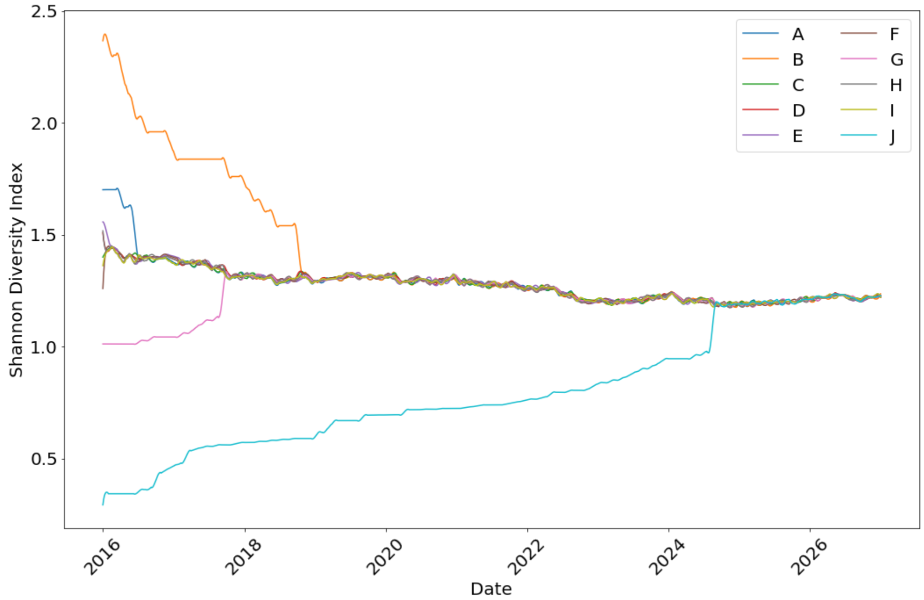

Fig. 2. Doctor Shannon index change chart

In our extended simulation running from 2016 to 2026, designed to reflect large-scale conditions, we convened local seminars quarterly within communities and global seminars annually across communities.Over the course of 120 months, it was found that consensus on Shannon indices was reached for only 64.3% of the doctors, from an initial pool of 1000, signifying a divergence in practice sharing.

These doctors coalesced into 18 distinct consensus groups based on their Shannon indices, with the largest group encompassing 643 physicians. The remaining 17 groups, although smaller in size, each achieved consensus internally. Doctors whose Shannon index differences were less than 0.15 by the end of the simulation were categorized into the same group and visually represented through color coding within the hierarchical network structure, as depicted in Fig. 3. This visualization illustrates not only the majority consensus but also the presence of multiple subgroups persisting with distinct practice-sharing patterns.

In our large-scale system analysis, we captured the number of doctors in each group and the varying times taken for different groups to converge. Groups with fewer than ten doctors generally converged within one month; hence, we have presented only those groups with more than ten doctors in Fig. 4.

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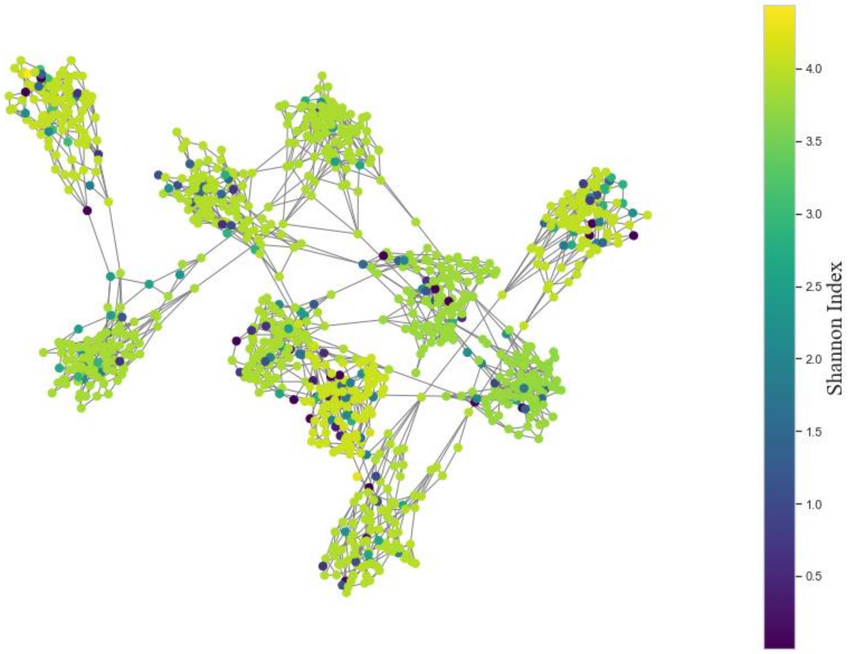

Fig. 3. Large-scale simulation

The Fig. 4 indicates that smaller groups (e.g., 10, 13, or 14 members) exhibit a faster median convergence time, suggesting that streamlined communication within tighter cohorts facilitates swifter consensus. Conversely, as group sizes expand (notably to 81, 98, or 643 members), both the median and interquartile range of convergence times increase, reflecting the broader range of opinions and the complexity involved in harmonizing these views within larger collectives. In the largest group, particularly, the significant spread and outliers in convergence times underscore the distinct challenges some doctors may encounter in aligning their practices with group consensus.Through experiments, we found that the convergence speed in large-scale systems has no obvious dependence on the number of communities and the number of doctors in the community.

In exploring the impact of seminar frequency on the convergence time of practice sharing among physicians(in the 18 final automatically formed groups), we applied a grid search methodology, considering only scenarios where the global seminar frequency does not exceed that of the local seminars to ensure the practical viability of the experimental setup.

The boxplots reveal a slight decrease in the median convergence time with an increasing frequency of local seminars, particularly when the global seminar frequency is set to every three months. Moreover, the shortest convergence times are observed at a global frequency of three months, indicating that frequent global interactions facilitate

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quicker consensus building. The reduction in interquartile range and decreased variability reflect an increased data concentration, suggesting that a tight seminar schedule positively influences convergence. Overall, the charts underscore the significance of increasing seminar frequency in shortening the convergence time between physicians. This trend suggests that frequent interaction through seminars may play a critical role in harmonizing practices among medical professionals. Furthermore, the data implies that strategic planning of educational activities could be pivotal in fostering a unified approach to healthcare within the community (see Fig. 5.).

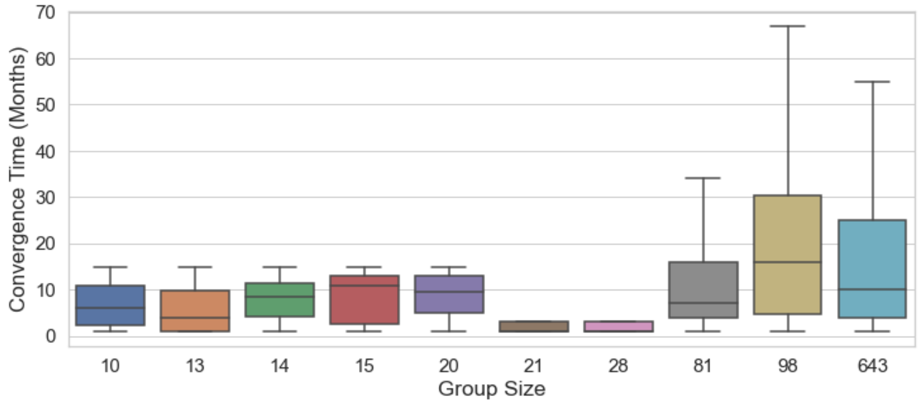

Fig. 4. Group convergence dynamics by Size

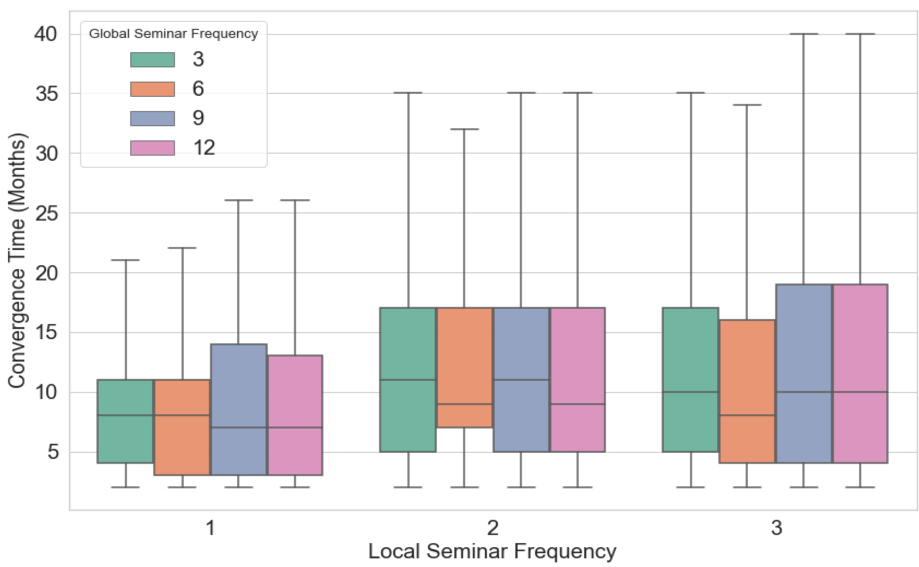

Fig. 5. Activity frequency versus convergence time

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DOI: 10.1007/978-3-031-63772-8_21

4 Discussion

In the preliminary small-scale experiment involving ten doctors, we simulated "Practice Sharing" by incorporating real activity timing information from the dataset. The simulated preference vectors closely aligned with the actual preference vectors, demonstrating the fundamental scientific validity of our modeling approach for "Practice Sharing" within the "Vertigo" dataset. Subsequently, we simulated the scenario of these ten doctors over a decade, where all participants eventually reached a consensus in diagnostic practice choices.

In the third phase of our study, we expanded the experiment to include 1000 doctors across ten communities. We examined the dependency of convergence time on the number of communities, the number of doctors within communities, and the frequency of activities. We found that both the number of doctors and the frequency of activities have a significant impact on convergence. In the model, individual physicians' learning is conceptualized as dynamic adjustments to their practice preference vectors. Collective learning is achieved through simulating interactions and information exchange among doctors, reflecting the social learning component in practice sharing.

5 Conclusion and future work

In this study, we have investigated the effectiveness of our model and approach in simulating the "Practice Sharing" process among doctors. Our model successfully replicated the evolution of doctors' preference vectors across networks of varying sizes, revealing the potential for achieving consensus within small groups and the complexities encountered in broader communities. This underscores the value of our approach in understanding and facilitating knowledge sharing and consensus formation in medical practice.

In our future work,building on the extension of practice preference studies, we are particularly interested in delving into the micro-level fusion and switching of practices. In this regard, introducing a research paradigm based on Distributed Constraint Markov Decision Processes (DEC-MDP) through reinforcement learning is intriguing. Regarding practice sharing, our focus extends to incorporating greater real-world complexity. We posit that interdisciplinary collaboration and information exchange can enhance the diversity and innovation of practices, while also acknowledging the potential for differentiation in practice preferences. Medical policies can shape physicians' practice preferences through the establishment of standardized procedures, promotion of specific treatment methods, or restrictions on certain practices. The recognition by authoritative bodies plays a significant role in the widespread adoption and acceptance of practices, with historical data suggesting significant shifts in physicians' practice preferences before and after the release of clinical guidelines. Additionally, factors such as medical culture, local ambitions, and funding reflect varying dependencies on the real world.

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DOI: 10.1007/978-3-031-63772-8_21

Acknowledgments. This research is financially supported by The Russian Science Foundation, Agreement #24-11-00272.

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DOI: 10.1007/978-3-031-63772-8_21

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