Improving Allocative Efficiency from Network Consolidation: A Solution for the Health Workforce Shortage

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Abstract

Background: Public hospitals are facing a critical shortage of health workers. The area-based network consolidations could be the solution to increase the system capacity for human resources by improving local allocative efficiency.

Methods: This study develops counterfactual simulations for area-based network allocations for the health workforce in 10,500 public hospitals in Thailand and examines improvements in allocative efficiency from the health workforce redistribution at different administrative levels such as sub-districts, districts, provinces, and health service areas. The workload per worker is calculated from the output measured by numbers of outpatient and inpatient cases and the input measured by numbers of health workers. Both output and input are weighted with their economic values and controlled for heterogeneity by regression analysis. The relative weights assigned to each outpatient and inpatient case reflect the labor cost of human resources assigned for each discharge. The relative weights for the health workforce are the multiplications of the work hours per week and the hourly earnings of each health profession. Finally, this study compares the workload per worker and economic values between the hospital-level or status quo scenario and the area-based networks or ex-ante scenarios.

Results: Network consolidations of the primary-level hospitals within the same district could reduce workload per worker by 7%. Another practical policy option is to consolidate similar hospital levels such as primary, first-level secondary, and mid-level secondary hospitals altogether within the same province which could result in the reduction of the workload per worker by 7%. The total economic value gained from consolidating similar hospital levels within the same province is about 15% of total labor cost in the primary hospitals.

Conclusion: This study illustrates the improvement in allocative efficiency of the health workforce in public hospitals from the area-based network consolidations. The results provide an insightful example of economic gains from reallocating the medical workforce within the same local areas. Major reforms are required such that the health care delivery units can automate their resources in corresponding to the population health needs through a strengthening gatekeeping system.

Keywords: health workforce, health resources, resource allocation, health catchment area, community health planning, community health network

Introduction

An important goal of human resource planning in a health system is to settle an adequate health workforce with balanced allocation in any specific administrative areas [1]. The major challenges of health resource allocation in Thailand are the scarcity of health workforce and the inequitable access to quality health care [2]. The country is facing the problem of higher demand for health services that exceeds the available capacity of the public health system [3].

Even though the geographical allocations of health workers in Thailand have been improved significantly over the last three decades with higher workforce availability, the number of health workers is still lower than the official requirement, and the public hospitals under the Office of the Permanent Secretary in the Ministry of Public Health (MOPH) still have chronic shortages in the health workforce. In addition to the insufficient budget [4], there are geographical allocation issues such that the health workforce is more concentrated in Bangkok and big cities and the inequity gap in proportions of the targeted population to medical doctors could reach almost ten times differential among provinces [5].

In particular, the shortage of nurses has been a critical issue for the Thai public health system, and the problem could be more severe [6,7]. Unfortunately, the nurse resignations are quite consecutively high due to the fact that the health system cannot retain skilled and experienced nurses, not because of the inadequate production of nurses [8]. A study of 19,912 registered nurses revealed that 10 percent of the surveyed sample would like to quit their career within the next two years [9]. Another study [10] found that the young and less-skilled nurses have a stronger intention of resignation. for having less time off, less job satisfaction, and higher stress. Other studies reported similar conclusions from community hospitals [11], a tertiary care hospital [12], and a university hospital [13].

In the future, Thailand will be facing higher demand for the health workforce in primary [14] and tertiary [15] hospital levels. The projections of demand and supply for medical specialists demonstrated severe shortages in almost all specialized medical professions as the consequences of the aged society [16]. Therefore, it is an urgency for the government to manage health workforce in order to improve allocative efficiency and achieve the desirable population health objectives.

Comparing with the other countries, Thailand has limited availability of health workforce. Appendix Table A1 and Figures A1-A2 show that the Thai medical workforce per 1,000 people is much lower than the developed countries or the selected countries in Asia. Appendix Table A2 illustrates that the workforce shortage in the MOPH hospitals is critical but seems to be mitigable if there is an improvement in allocative efficiency due to variations in the shortage severity at different hospital levels.

Successful health resource planning requires not only the balance in both quantitative and qualitative goals of the health workforce management but the adaptation to varying health system needs. Certainly, the effective reallocation for the supply of medical workers in accordance with the demand for health care will lead to the more desirable clinical outcomes [17].

This study reports efficiency gains and associated economic values from the area-based human resource allocation of hospitals under the Office of the Permanent Secretary, the MOPH. The area-based network of the health workforce in this study is a simulation application of consolidating the public hospitals within local administrative areas. It is a counterfactual quantitative exercise to measure the hospital outputs per worker and subsequent results of reduction in workload per worker from network allocation scenarios. The network consolidation should simultaneously mitigate the health workforce shortage and enhance allocative efficiency of the health workers within their local areas from improvements in the workload per worker. Due to the health workforce shortage in public hospitals in Thailand, the lower workload per worker implies increase in workforce sufficiency rather than decrease in efficiency of the health system.

In fact, the area-based network of the health workforce is not a new concept for Thailand. It has been developed and implemented by the health system and medical staffs to collaborate in the district health administration systems for many years [18-21]. Jithitiikulchai (2020) [22] studied the area-based network consolidations for the health workforce in the MOPH hospitals. The author [22] found that the shortage situation is severe, and that the shortage could be mitigated from network reallocations. However, the analysis in the study [22] was considered by each medical profession such as doctor, nurse, dentist, pharmacist, and others. Thus, this pioneered work did not consider the aggregated output of health care service delivery units relative to the total health workforce, but only investigated by medical profession based on the number of health workforce relative to the minimum manpower requirement.

Therefore, this study endeavors to quantify whether and how the area-based resource allocation at different levels of hospital services and administrative areas could mitigate the health workforce shortage in terms of per capita workload reductions and proposes a general framework for the area-based network consolidation simulations. Specifically, this study develops the counterfactual simulation model to compares the workload per worker between (a) the hospital-level averages (status quo) and (b) the area-based network averages after consolidations at different levels of hospital services within the local administrative areas (ex-ante). This approach is an application of the gatekeeping concept to optimally allocate resources according to the demand and supply of health care services to mitigate the shortage problem of the health workforce.

The methodology is straightforward, duplicable, and scalable. Simple linear regression approach is used to estimate the weights of output and input reflecting their economic values. The status quo and ex-ante scenario comparisons use basic arithmetic operations. The simple economic valuation could help to recommend consolidation options that provide higher monetary values. This analysis could be an aspiring example of network consolidations for other countries facing a shortage in health workforce.

Methods

This study develops the counterfactual network simulation exercises for the area-based health workforce allocation at different levels of hospital services within various levels of local health administrative areas. The objective is to measure allocative efficiency from redistributing the health workforce to improve health system's capacity.

The network consolidation approach is considered an application of the gatekeeping system to manage health system resources in corresponding to the demand for health care services and the workforce supply capacity within each of the local system networks. This study assumes an efficient gatekeeping system such that local health systems could automate the seamless referral system for the outpatient (OP) and inpatient (IP) patients and, accordingly, allocate the area-based workforce to minimize the shortage of the workers.

The administrative area levels in this study follow the MOPH system which are the sub-district, district, province, and health service area levels. There are five hospital levels which are primary, first-level secondary, mid-level secondary, high-level secondary, and tertiary.

This study considers network consolidations within local administrative areas with different hospital classifications:

1. All hospital levels altogether

2. Only within the same hospital level

3. Similar hospital levels

    3.1) Type A: {Primary, First-level Secondary} and {Mid-level Secondary, High-level Secondary, Tertiary}

    3.2) Type B: {Primary, First-level Secondary, Mid-level Secondary} and {High-level Secondary, Tertiary}

The counterfactual simulation for network consolidation analysis provides comparisons of the "workload per worker" between (a) the hospital-level averages (status quo) and (b) the network averages after consolidations at different levels of hospitals and administrative-areas (ex-ante). See Supplementary Material Figure S1 for an illustrative example of local network by the four hospitals in the same area.

The workload per worker is the output divided by input, in which this study calculates both output and input to reflect their costs of human resources. The weights of each outpatient and inpatient case are the relative cost of workforce assigned for each discharge. The weights of the health workforce are the weekly work hour multiplied with the hourly earnings of each health occupation. Using the relative weights implicitly assume that the relative costs could capture the differences in severity of the medical treatment cases and intensity of the workload.

The output is the weighted aggregation of medical treatment cases, where weights reflect the estimated labor costs. Thus, the outputs of hospital or area-based network are the aggregation of the OP and IP cases weighted to reflect the relative workforce costs allocated to each discharge.

The approach used to measure output in this study follows the case mix index (CMI) concept that provides a standard reference for the standard IP costs for the diagnosis-related group (DRG) [23]. Similarly, this study calculated the average costs with the regression models separately for the five hospital levels within each of the OP or IP categories. Thus, the OP and IP cases can be weighted with the standardized costs given observable characteristics and then aggregated as the total output of each hospital or network.

The average costs of each treatment case from the regression analysis are determined by the observable attributes such as principal diagnosis (PDx), sex and age of patients, service time, service type, insurance type, number of days admitted (only IP treatments), and health region. The log-linear cost regression functions are calculated separately for OP and IP services from five different hospital levels to standardize relative weight values to each medical treatment case. For instance, medical treatments in higher-level hospitals tend to be more costly than those in the primary hospitals such that the cost differentiations are emulated through regression models of different hospital levels. The same proposition applies to separate cost estimations for OP and IP categories. As the cost from each treatment case is the total cost reported from hospitals, this study multiplies the predicted costs of each OP and IP case with the hospital-level share of labor cost to reflect workloads through the labor cost. Technical details on output measurement and cost regressions are available in the Supplementary Material.

The input factor in this study is the total number of health workers in which each medical profession is weighted with their regional averages of hourly earnings and work hours per week. Thus, the aggregation of the weighted numbers of health workers is the total workforce of hospitals or area-based networks. The average work hours per week and average earning per hour are calculated with the regression models controlling for observable characteristics of the health workers in the public sector aged 15-64, using the national labor force surveys. Technical details on workforce measurement and relative weights are provided in the Supplementary Material.

The workload per worker is calculated as the ratio of the weighted aggregate medical treatment output and the weighted number of workforces. This study compares workload per worker between the hospital-level average before network consolidations (status quo) and the averages after network consolidations at different administrative-area levels (ex-ante). The counterfactual network consolidation simulations quantify the area-based health workforce allocation within the local administrative areas by categories of hospital levels. The hypothesis in this study is that the network consolidation within the same administrative areas could improve the health system efficiency by alleviating the shortage of health workforce.

This study calculates average reductions in workload per worker as the percentage differences between the averages of workload per worker from the status quo and ex-ante scenarios, whereas the unit of measurements is the OP case in primary hospitals. The standardized measurement unit, using the average labor costs for OP treatments in primary health care units to calculate the number of OP cases in primary hospitals, allows comparisons of the OP and IP services across different hospital clustering levels.

Finally, this study estimates the economic value to compare the network consolidation options across different administrative areas and hospital-level classifications, using the status quo situation as the baseline scenario. The reduction in workload per worker can be valued financially by multiplying the total workloads reduced from network consolidation with the average labor costs. The reduced number of total workloads are the multiplications of the number of health care service delivery units, average health workers per service delivery unit, average workload per worker, and the percentage reduction in workload per worker. The workload and labor costs are in units of OP cases in primary hospitals. Technical details on area-based network allocation and economic evaluation are described in the Supplementary Material.

Data

The case-based discharge data from the Information and Communication Technology Center of the MOPH used in this study covers principal diagnosis (PDx), sex, age, service time (office hours or after hours), service type (walk-in, referral, among others), insurance type (Universal Coverage Scheme, Civil Servant Medical Benefit Scheme, Social Security Scheme, and others), number of days admitted (IP treatments only), and costs of each treatment case. The OP and IP cases are the discharges in the fiscal year 2019.

Numbers of each medical profession such as the doctor, nurse, dentist, pharmacist, and other medical occupations are the hospital-level data from the Human Resource Management Division of the Office of the Permanent Secretary, the MOPH. There are 100,320 nurses, 16,593 doctors, 7,906 pharmacists, and 4,662 dentists who worked in the hospitals for the fiscal year 2019 as reported in Appendix Table A2.

The average hourly earnings and work hours per week of each medical profession are calculated from the quarterly Labor Force Survey (LFS) 2002Q1 to 2020Q1 of the National

Statistical Office. The workers aged 15-64 employed in the public sector are selected for each medical profession using the International Standard Classification of Occupations, ISCO-88 codes. The health workforce weights as adjustment factors are reported in Table S3 of the Supplementary Material.

Results

This study uses the medical case data from 10,500 public hospitals under the Office of the Permanent Secretary, MOPH, across geographical units and health regions. The output is based on 284,273,598 OP discharges and 18,971,271 IP discharges in the budget year 2019. The OP and IP cases are weighted with their estimated costs, in which the estimated OP and IP costs are controlled for observable heterogeneity through linear regression estimations separately for each of five hospitals levels. Supplementary Material Tables S4-S5 provide the regression results of the cost of OP and IP cases.

The output, the aggregations of weighted average costs of OP and IP treatments in each hospital are normalized with the average labor cost of the OP cases in primary hospitals and resulted in 1,204,133,398 normalized OP discharges in primary hospitals as the standardized output unit. There are 155,377 health workers calculated from the total workforce weighted with their regional averages of work hours per week and earnings per hour of each occupation. The output per worker is a standard unit of measurement calculated as the "OP cases in primary hospitals per worker" used in comparing the status quo and ex-ante scenarios across different hospital and geographical administrative area levels. Both output and input estimates reflect the labor resources expended for medical treatments in the fiscal year 2019.

The results from the consolidation of all hospital levels altogether illustrate that the networking at the district levels can reduce the average workload per worker by about 4.4%

on average or reduce from 7,924 to 7,785 OP cases in the primary hospitals, as shown in Table 1. Meanwhile, at the province and health region levels, the workforce consolidation could reduce by 1.5% and 1.6%. However, the networking at the sub-district level has no impact on average, such that the primary-level OP cases per worker are about the same.

Table 1: Area-based network allocation of all service levels

All Levels	Units	Average workforce	Total normalized OP cases	Average OP cases per worker	Average reduced OP cases per worker
Hospital	10,500	393	4,751,255	7,924	
Sub-district	7,025	396	4,770,658	7,920	0.1%
District	878	508	5,831,026	7,785	1.8%
Province	76	2,616	22,294,363	7,808	1.5%
Health region	12	13,406	99,726,840	7,801	1.6%

Note: The reduced OP cases per worker are the percentage differences of the average cases per worker after the consolidation (ex-ante) compared with the average cases per worker of hospitals (status quo).

The results from the networking within the same hospital-levels are illustrated in Table 2. The results show that the consolidation of workforce at the primary level and the approach of networking at the district, province, and health region levels could reduce workload per worker by 7%, 10%, and 14%, respectively. For the first-level secondary hospitals, area-based networking cannot reduce the workload. For the mid-level secondary hospitals, networking at the administrative levels of the province and health region could reduce workload per worker by 2-3%. For the high-level secondary and the tertiary hospitals, the area-based network consolidations cannot reduce the workload quantity per worker.

Table 2: Area-based network allocation by each service level

Each level	Units	Average workforce	Total normalized OP cases	Average OP cases per worker	Average reduced OP cases per worker
1. Primary					
Hospital	9,609	3	13,709	5,759	
Sub-district	6,548	5	22,807	5,791	-0.6%
District	877	39	193,440	5,379	6.6%
Province	76	421	2,213,098	5,164	10.3%
Health region	12	2,298	11,034,260	4,929	14.4%
2.1 First-level Secondary					
Hospital	508	78	420,186	5,510	
Sub-district	508	78	420,186	5,510	0.0%
District	502	79	430,050	5,510	0.0%
Province	66	725	4,156,579	5,483	0.5%
Health region	12	3,120	16,650,573	5,461	0.9%
2.2 Mid-level Secondary					
Hospital	264	117	490,123	4,469	
Sub-district	264	117	490,123	4,469	0.0%
District	260	119	496,075	4,469	0.0%
Province	65	603	2,578,542	4,371	2.2%
Health region	12	2,367	9,974,729	4,329	3.1%
2.3 High-level Secondary					
Hospital	84	529	3,908,967	8,462	
Sub-district	84	529	3,908,967	8,462	0.0%
District	84	529	3,908,967	8,462	0.0%
Province	61	710	6,172,210	8,476	-0.2%
Health region	12	3,073	26,335,503	8,484	-0.3%
3. Tertiary					
Hospital	35	1,158	17,252,208	14,037	
Sub-district	35	1,158	17,252,208	14,037	0.0%
District	35	1,158	17,252,208	14,037	0.0%
Province	34	1,165	17,295,997	14,038	0.0%
Health region					-0.2%

12	3,388	39,571,635	14,068

Note: The reduced OP cases per worker are the percentage differences of the average cases per worker after the consolidation (ex-ante) compared with the average cases per worker of hospitals (status quo).

In an effort to network workforce in similar hospital levels, there are two options, {Primary, First-level Secondary} of Option A and {Primary, First-level Secondary, Mid-level Secondary} of Option B, as illustrated in Tables 3a-3b. The results show that both options of network consolidations for similar hospital levels could reduce the average workload per worker for the lower hospital levels. When combined at the province level, Option A could reduce the workload by 6%, while Option B could reduce the workload by 6.7%, on average.

However, both options could reduce the average cases per worker only by 1-2% within the health regional networks in the upper hospital levels, which are {Mid-level Secondary, High-level Secondary, Tertiary} of Option A and {High-level Secondary, Tertiary} of Option B.

Table 3a: Area-based network allocation by clustered service level (Option A)

Levels	Units	Average workforce	Total normalized OP cases	Average OP cases per worker	Average reduced OP cases per worker
Primary and First-level Secondary					
Hospital	10,117	37	196,712	5,645	
Sub-district	6,803	40	211,733	5,656	-0.2%
District	878	91	478,724	5,421	4.0%
Province	76	1,071	5,972,216	5,296	6.2%
Health region	12	5,312	27,267,885	5,218	7.6%
Mid-level Secondary, High-level Secondary, and Tertiary					
Hospital	383	683	8,451,506	9,744	
Sub-district	383	683	8,451,506	9,744	0.0%

District	376	710	9,055,009	9,750	-0.1%
Province	76	1,697	17,177,190	9,627	1.2%
Health region	12	8,351	73,694,039	9,527	2.2%

Table 3b: Area-based network allocation by clustered service level (Option B)

Similar levels	Units	Average workforce	Total normalized OP cases	Average OP cases per worker	Average reduced OP cases per worker
Primary, First-level Secondary, and Mid-level Secondary					
Hospital	10,381	55	263,619	5,373	
Sub-district	6,940	58	279,078	5,378	-0.1%
District	878	120	585,779	5,092	5.2%
Province	76	1,432	7,474,182	5,011	6.7%
Health region	12	7,364	35,889,151	4,971	7.5%
High-level Secondary and Tertiary					
Hospital	119	861	10,965,434	11,410	
Sub-district	119	861	10,965,434	11,410	0.0%
District	116	896	11,757,623	11,418	-0.1%
Province	76	1,260	16,639,308	11,442	-0.3%
Health region	12	6,168	66,066,136	11,290	1.1%

Note: The reduced OP cases per worker are the percentage differences of the average cases per worker after the consolidation (ex-ante) compared with the average cases per worker of hospitals (status quo).

Economic valuation of network consolidation options

The economic valuation can be compared between the status quo and ex-ante scenarios and can appraise the network consolidation options. For each network consolidation option, the aggregated reduction in a standardized unit of OP cases conducted at primary hospitals are calculated using the multiplication of the reduced primary OP cases per worker, average primary OP cases per worker, the average number of workforces in each service-delivery unit, and the total number of units. In the end, we obtain the aggregate numbers of reducible primary OP cases multiplied with the average labor cost per OP case at primary hospitals, the economic value gained from the network consolidation.

In Table 4 below, the total reductions in number of primary OP cases, which could be obtained from each network consolidation option comparing with the status quo scenario, are illustrated. The most reduced number in the aggregate workloads occurs from consolidating all hospital levels altogether. However, combining all hospital levels seems unrealistic and unpractical. The more reasonable options are to network similar hospital levels and combine within the provinces or health service areas.

Table 4: Total number of primary OP cases gained from different network consolidation levels

			Similar Hospital Levels	
	All Levels	**Each Level**	**Option A**	**Option B**
Sub-district	22,056,449			
District	62,457,295	12,099,738	14,689,296	26,627,800
Province	23,289,839	21,355,110	41,627,599	33,242,766
Health region	20,079,491	23,146,822	46,282,149	42,137,805

Note: The unit of measurement is the OP case at the primary hospitals.

Table 5 illustrates the economic values in Thai Baht and US dollar in correspondence with Table 4. A practical alternative with high economic outcomes is the application of combining hospitals with similar hospital levels at the provincial level. The calculation shows that, if comparing with the aggregate labor cost incurred at hospitals in the same budget year, the network consolidations of similar hospital levels within the same provinces could gain about 15-18% of total labor cost in the primary hospitals or 10 billion Thai Baht.

Table 5: Economic values from different network consolidation levels (in million THB and USD)

	All Levels		Each Level		Similar Hospital Levels			
					Option A		Option B	
	THB	USD	THB	USD	THB	USD	THB	USD
Sub-district	978	30						
District	2,770	86	537	17	651	20	1,181	37
Province	1,033	32	947	29	1,846	57	1,474	46
Health region	890	28	1,026	32	2,052	64	1,869	58

Note: The THB/USD is 32.3 which is the 2011-2020 average.

Discussion

The area-based network consolidations can redistribute the health workforce and assist in providing health care services with improvements in allocative efficiency of human resource administration. Suggested by the most practical results from the analysis in this study, networking the primary-level hospitals within the same district could reduce workload per worker by 7% on the national average. Another feasible option is the method of consolidating similar hospital levels such as primary, first-level secondary, and mid-level secondary hospitals within the same province which is estimated to reduce the workload per worker by 7%. Nonetheless, its implementation requires the strengthened primary health care units of the primary-level hospitals within each district.

Conceptually, we assume that the network consolidations occur in the situation that we have the efficient gatekeeping system to optimize resources according to the demand for health care service and the workforce supply capacity within each network. However, we should realize that the health service units are still independent of each other in planning, budgeting, and performance assessment. In addition, the current health system does not allow such flexibility to reflect in the promotion and career path for public health workers in Thailand.

Therefore, this requires what Leerapan et al. (2018) [24] proposed as "major reforms of MOPH care delivery models" such that the health care delivery units can adjust and adapt their resources and services in corresponding to the population health needs. Leerapan et al. (2018) [24]'s proposal includes the capacity reallocation of health care delivery teams to be enlarged in the areas with excess demand and to be reduced in the areas with excess supply. This proposal of "major reforms of MOPH care delivery models" is conceptually consistent with the allocative efficiency; the health system utilizes the management capacity to establish and prioritize local objectives to redistribute health system resources corresponding to the demand-supply gaps of health workforce.

Noree et al. (2017) [25] defined distinguished properties of the desirable health care delivery system as a seamless health service network of an integrated system of primary, secondary, and tertiary hospitals. Pooling resources and planning through the management information system within a local health care network are critical for a robust referral management system with the gatekeeping application. Both Noree et al. (2017) and Leerapan et al. (2018) [24-25] aligns with the goal of the "value-based health care" concept [26-27], which is a health care delivery model to maximize the value of care for patients and minimizing the cost of health care.

The practical possibilities in my opinion are to consolidate primary hospitals within each district, similar hospital levels within each province, or a mixture of both. Although the evaluations in this study center on the results at average, this study can provide some guidance of the policy options for optimal allocation of public health workers to mitigate workforce shortage. A good policy is not one-size-fits-all. It requires decentralization for the provincial and district health systems to have their autonomy over decision-making processes and be equipped with accountability to monitor and evaluate their performance through the health and management information systems.

The area-based networking approach at the district or provincial level could add a commuting and time burden to the health workers. This is inevitably undeniable. Therefore, we need financial incentives, career advancement mechanisms, and team development programs, among others, to facilitate the local health care system development. See [28-37] for evidence of the effective financial and non-financial incentives in Thailand and developing countries.

In addition, the gatekeeping system must consider the potentially increased travel cost burdens to the patients especially the poor living in the remote rural areas. The primary hospitals are available in every sub-district of Thailand in which those patients who can commute to their sub-district hospital should be able to access to the district-level primary healthcare network. However, the higher-level hospitals mostly locate in the city areas. The transportation services for referrals are required to support the health care accessibility of the poor and vulnerable people.

Finally, any country with community health network policies should have a national strategic plan for area-based health system development that aligns with the national human resource plan. Not only the more equitable distribution is required for health workforce management across geographical and administrative areas, but also the more fiscal resources to produce the medical workforce to solve the shortage severity, as we can observe from Appendix Table A1 and Figures A1-A2 which illustrated that Thailand has too low medical workforce. The author strongly encourages the health workforce organizations to call out for reprioritizing the more national budget for the health system to improve the desirable population health outcomes.

Limitation

First, this study has some limitations on total output calculations. Health workforce positions have the responsibility not only on treatment service delivery used in this study. They also have some other tasks such as health promotion and disease prevention services, and administrative works, among others. Due to data limitations of the addition roles of health personnel, this study cannot consider other duties beyond the OP and IP discharges.

Second, the area-based network consolidations in this study assumed that the health workforce could move freely within the network to serve the local health care needs. However, the calculations are the technical results for the policymakers to consider policy and program options on human resource management. It requires considerate evaluations of positive and negative externalities that potentially occurred to the health workers within each hospital and the local area. The practical possibilities seem to consolidate primary hospitals within each district, similar hospital levels within each province, or a mixture of both. Instead of the workforce relocation, the robust referral system could assign patients to the most appropriate hospitals at the time. This could be actualized with the digital transformation of the local health systems

Third, the calculations in this study did not explicitly consider the capital inputs of hospitals. It is perhaps difficult in terms of conceptualization to incorporate the capital component into the cost regression models. This study reflects the capital factor by providing a more realistic consolidation within the same or similar hospital levels to mirror the capital differences between hospital levels. Thus, it is recommended by the author that future studies should reckon with the capital of hospitals.

Lastly, this study uses the estimated labor cost for weights of each OP and IP case. However, Porter (2006, 2010) [26-27] suggested that achieving the goal of health care delivery requires that the value determinant should be the health outcomes achieved per every monetary unit spent. Therefore, the future research can measure the value of each discharge with the framework for performance improvement in health care that creates value for patients, measured by the outcomes achieved, not inputs nor volume of services delivered.

Conclusion

This study evaluates shortage mitigation from the area-based network of health workers. The analytical results confirm improvement in allocative efficiency of the health workforce in the MOPH hospitals. The economic valuation reveals that consolidating similar hospital levels within the same province is an optimal solution. The benefits from efficient area-based networks are equal to 15-18% of total labor cost in the primary-level hospitals.

Abbreviation

CSMBS: Civil Servant Medical Benefit Scheme; MOPH: Thai Ministry of Public Health; PDx: principal diagnosis; SSS: Social Security Scheme; UCS: Universal Coverage Scheme

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Availability of data and materials

The datasets used for this study are available from the corresponding author upon reasonable request and with the authorized approvals from the government offices which own the original raw data.

Author's contributions

TJ solely worked on the study.

Ethics approval and consent to participate

Not applicable as secondary and anonymous data was used in the study.

Consent for publication

Not applicable.

Competing interests

The author declares to have no competing interests.

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Appendix

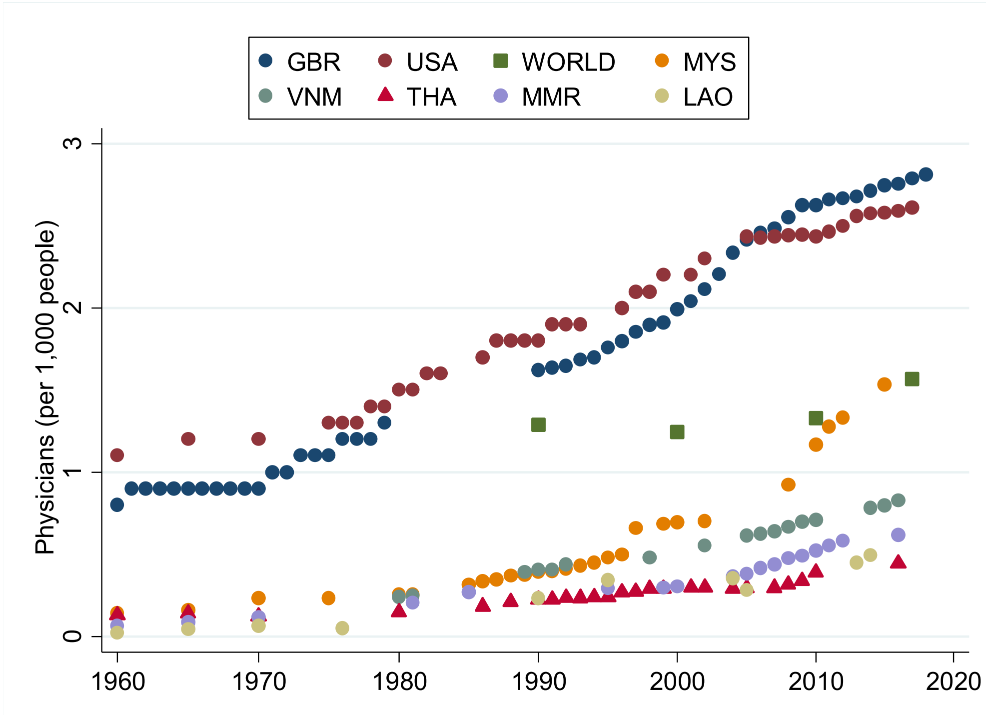
Table A1: Medical workforce per 1,000 people

	Doctor	Nurse	Dentist	Pharmacist
Thailand	0.50	2.40	0.10	0.20
OECD countries				
Austria	5.16	8.10	0.57	0.69
Switzerland	4.27	17.60	0.54	0.55
Germany	4.14	13.30	0.80	0.62
ASEAN countries				
Brunei	1.50	7.80	0.23	0.12
Singapore	1.90	6.40	0.33	0.39
Malaysia	1.20	3.30	0.36	0.43

Thailand as %	Doctor	Nurse	Dentist	Pharmacist
OECD countries				
Austria	10%	30%	18%	29%
Switzerland	12%	14%	19%	36%
Germany	12%	18%	13%	32%
ASEAN countries				
Brunei	33%	31%	43%	167%
Singapore	26%	38%	30%	51%
Malaysia	42%	73%	28%	47%

Source: Health at Glance Thailand 2017. Strategy and Planning Division of Office of the Permanent Secretary, Ministry of Public Health

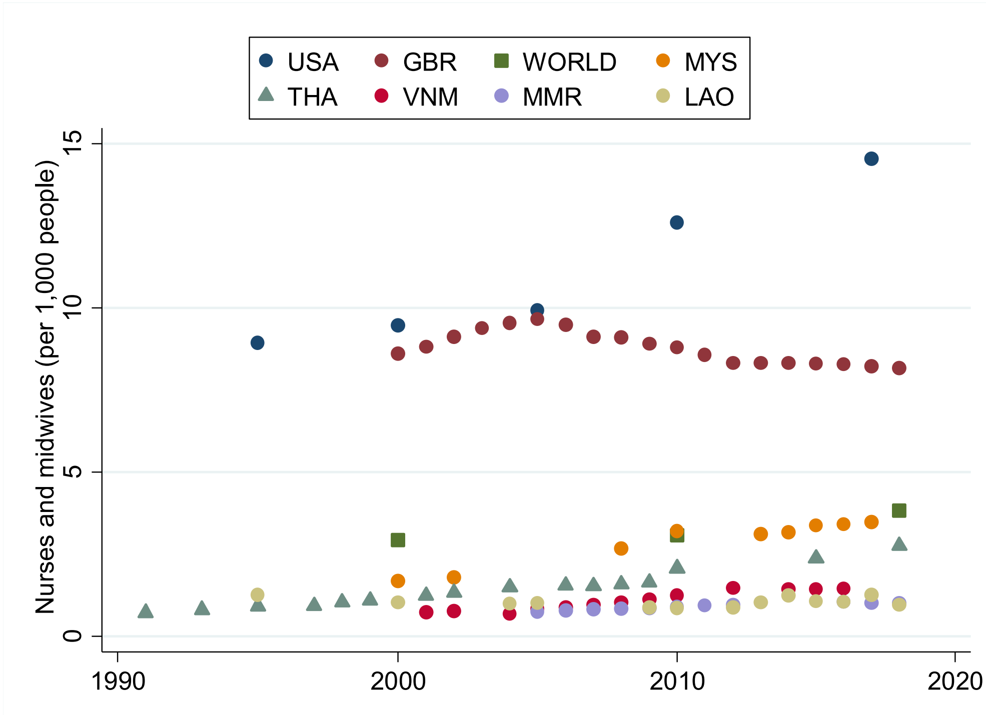
Figure A1: Medical doctors per 1,000 people, 1960-2018



Note: GBR=Great Britain, USA=United States of America, WORLD=global average, MYS=Malaysia, VNM=Vietnam, THA=Thailand, MMR=Myanmar, and LAO=Laos.

Source: World Development Indicators, The World Bank

Figure A2: Nurses and midwives per 1,000 people, 1991-2018



Note: USA=United States of America, GBR=Great Britain, WORLD=global average, MYS=Malaysia, THA=Thailand, VNM=Vietnam, MMR=Myanmar, and LAO=Laos,

Source: World Development Indicators, The World Bank

Table A2: Shortage in health workforce of the hospitals under the Office of the Permanent Secretary, MOPH

	Doctor	Dentist	Pharmacist	Nurse
1. Primary				
Shortage severity index	*-2%*	*-35%*	*26%*	*-52%*
Health workers	14	5	8	9,826
Hospitals	3	3	3	9,633
2.1 First-level Secondary				
Shortage severity index	*-25%*	*-19%*	*-3%*	*6%*
Health workers	3,924	1,866	2,626	23,359
Hospitals	508	508	508	508
2.2 Mid-level Secondary				
Shortage severity index	*-16%*	*-17%*	*-2%*	*2%*
Health workers	2,869	1,231	1,714	15,902
Hospitals	265	265	265	265
2.3 High-level Secondary				
Shortage severity index	*-21%*	*0%*	*-1%*	*4%*
Health workers	4,362	907	1,881	25,394
Hospitals	84	84	84	84
3. Tertiary				
Shortage severity index	*-8%*	*-6%*	*-4%*	*-19%*
Health workers	5,424	653	1,677	25,839
Hospitals	36	36	36	36
All levels				
Shortage severity index	*-21%*	*-16%*	*-2%*	*-47%*
Health workers	*16,593*	*4,662*	*7,906*	*100,320*
Hospitals	*896*	*896*	*896*	*10,526*

Note: The shortage intensity index (% of minimum manpower required) is the average of $\frac{(n_{i.j}-lb_{i,j})}{lb_{i,j}} \times 100$. For the hospital i and health profession j, the $n_{i.j}$ is the number of health worker, and the $lb_{i,j}$ is the minimum manpower requirements.

Source: Jithitikulchai T. Area-based network allocations: a solution to mitigate the shortage of health workforce. Journal of Health Systems Research 2020;14(3):243-73.

Improving Allocative Efficiency from Network Consolidation: A Solution for the Health Workforce Shortage

SUPPLEMENTARY MATERIAL

Methods

This study endeavors to quantify the reduction of workload per worker from the area-based network allocation. The analysis conducts the counterfactual simulations to compare the workload per worker between (a) the hospital-level averages (*status quo*) and (b) the area-based network averages after consolidations at different administrative-area and hospital levels (*ex-ante*).

This study enumerates the reductions in workload per worker to evaluate economic gains from the area-based health workforce allocation policy at different levels of hospital services within the local administrative areas. This approach is an application of the gatekeeping concept to manage resources according to the demand for health care service and the workforce supply capacity within each network.

This study calculates the workload per worker from the output as the weighted numbers of outpatient (OP) and inpatient (IP) cases, divided by the input as the weighted numbers of health workers. This calculation applies to both the hospital and area-based network averages.

The output of the health system in this study is the workload which covers OP and IP services. This study applies the case mix index (CMI) approach to assign relative weights to the OP and IP cases to reflect the relative human resources allocated for each medical treatment case. The output weights are calculated from the log-linear cost regression models to standardize the costs for human resources used in each OP or IP case. The aggregations of outputs for the hospitals or the local health system networks can be standardized with the average labor cost of the OP cases at the primary-hospital level to have the same measurement unit for comparisons across levels of administrative areas and hospitals, and OP/IP treatment categories.

The input factor is the weighted numbers of health workers, whereas the weights are the multiplications of average hourly earnings and average work hours per week. The worker or input in this study covers medical doctors, nurses, dentists, pharmacists, and other medical professions.

Conceptually, the calculations of both output and input reflect their economic values. The output weights are calculated from the observed characteristics through the cost regression models of OP and IP cases. Similarly, the calculations of the input weight components, averages of hourly earnings and weekly work hours of each medical profession, are calculated with the regression models of the health workers in the public sector.

Finally, this study compares the workload per worker from the scenarios before network consolidations (status quo) and after network consolidations (ex-ante). The counterfactual area-based network simulations are calculated for different hospital classifications: all hospital levels, only the same hospital level, and similar hospital levels. The administrative area levels in this study cover the sub-district, district, province, and health service area.

The network allocation for the health workforce considers the hospital output per worker as the baseline to evaluate the efficiency gain of human resource pooling within the area-based network. To estimate the economic value, the reductions of workload per worker can be straightforwardly calculated for the total workload reductions and then multiplied with the average labor costs. Therefore, we can compare the network consolidation options across different administrative areas and hospital-level classifications from the economic gain differentials.

This study assumes an efficient gatekeeping system such that local health systems could distribute the OP and IP patients and, accordingly, allocate the workforce to minimize the shortage of the workers. Assuming that the health professions could be perfectly substituted is unrealistic. Nevertheless, this study endeavors to quantify the health workforce resources as the total budget allocated to the health system. Therefore, instead of making the perfect substitution assumption, this study explicitly assumes the gatekeeping system efficiency.

Output of medical service in public hospitals

The main output equation can be described as following:

$$\hat{y}_i = \widehat{OP}_i + \widehat{IP}_i$$

where $\hat{y}_i$ is the estimated quantity of medical service outputs for hospital i, which composes of $\widehat{OP}_i$ as the weighted number of outpatient cases and $\widehat{IP}_i$ as the weighted number of inpatient cases.

The weighted number of outpatient cases $\widehat{OP}_i$ is calculated from

$$\widehat{OP}_i = \hat{C}_i^{OP} Q_i^{OP} \times shr\_labor\_cost_i$$

which $\hat{C}_i^{OP}$ is a vector of standardized total costs for each outpatient discharge calculated by hospital i, Q_i^{OP} is a multipliable vector of ones for all outpatient cases in hospital i, and $shr\_labor\_cost_i$ is the hospital-level share of labor cost. Each element of Q_i^{OP} represents outpatient case which implicitly contains attributes as regressors shown in Table S1.

Table S1. Regressors for the log cost regression functions of outpatient and inpatient treatments

Variable	Description	Outpatient	Inpatient
PDX_{ICD-10}	ICD-10 Principal Diagnosis (PDx) codes of 140 disease categories	×	×
age	Age	×	×
age^2	Age squared	×	×
$female$	Sex	×	×
$intime$	Dummy variable of service time (1=office hours, 2=out-office hours)	×	×
$typein$	Dummy variables of service type (1=walk-in, 2=by appointment, 3=refer from other hospital, 4=refer from emergency service or EMS)	×	×
$instype$	Dummy variables of insurance type (1=UCS, 2=CSMBS and other state schemes, 3=SSS, 4=OOPE)	×	×
$days\_admit$	Days admitted		×
$days\_admit^2$	Days admitted squared		×
$area\_id$	Dummy variables of health regions (12 areas)	×	×

Source: OP and IP discharges in the budget year 2019, ICT Center, MOPH

Note: UCS = Universal Coverage Scheme, CSMBS = Civil Servants Medical Benefit Scheme and other relevant health insurance programs, SSS = Social Security Scheme, and OOPE = Out-of-pocket expenditure.

Therefore, the estimated $\hat{C}_{OP}$ can be calculated from the following linear regression model of the log-transformed total cost of each OP discharge:

$$\log\,(C_{OP}) = \alpha_0 + \sum_{j=2}^{140} \alpha_{PDX_j^{ICD-10}} \times I\left(PDX_j^{ICD-10}\right) + \alpha_{age} \times age + \alpha_{age^2} \times age^2$$

$$+ \alpha_{female} \times I(female) + \ \alpha_{intime} \times I(intime) + \sum_{k=2}^{4} \alpha_{typein_k} \times I(typein_k)$$

$$+ \sum_{l=2}^{4} \alpha_{instype_l} \times I(instype_l) + \sum\nolimits_m \alpha_{area\_id_m} \times I(area\_id_m) + u$$

where $\log(C_{OP})$ is a log-transformed vector of the reported total cost for each outpatient discharge, with regressors from Table S1, where u is a vector of stochastic component independently distributed by a normal distribution with zero mean and constant variance, or $u \sim N(0, \sigma_u^2)$. The $\left(\alpha_0,\ \{\alpha_{PDX_j^{ICD-10}}\}_{j=2}^{140},\ \alpha_{age},\ \cdots\ ,\ \{\alpha_{area\_id_m}\}_m\right)$ are the outpatient cost regression parameters to be estimated. The $j,\ k,\ l,$ and m denote the subscripts for dummy variables of ICD-10 Principal Diagnosis (PDx) code, service type, insurance type, and health service area of outpatient discharges. Thus, the standardized cost controlled for observable heterogeneity in disease, patient, service, and areas: $\hat{C}_{OP}$ could be obtained from the fitted regression model.

Similarly, the weighted number of inpatient cases $\widehat{IP}_i$ is calculated from

$$\widehat{IP}_i = \hat{C}_i^{IP} Q_i^{IP} \times shr\_labor\_cost_i$$

which $\hat{C}_i^{IP}$ is a vector of standardized total costs for each inpatient discharge in hospital i, Q_i^{IP} is an all-ones multipliable vector of all inpatient cases in hospital i, and $shr\_labor\_cost_i$ is the hospital-level share of labor cost. Each element of Q_i^{IP} represents inpatient case which contains attributes as regressors in Table S1 above. Therefore, the estimated $\hat{C}_{IP}$ can be calculated from the following linear regression model of the log-transformed total cost of each IP discharge:

$$\begin{aligned}\log\left(C_{IP}\right) = \beta_0 + \sum_{j=2}^{140} \beta_{PDX_j^{ICD-10}} \times I\left(PDX_j^{ICD-10}\right) + \beta_{age} \times age + \beta_{age^2} \times age^2 \\ + \beta_{female} \times I(female) + \beta_{intime} \times I(intime) + \sum_{k=2}^{4} \beta_{typein_k} \times I(typein_k) \\ + \sum_{l=2}^{4} \beta_{instype_l} \times I(instype_l) + \beta_{days\_admit} \times days\_admit \\ + \beta_{days\_admit^2} \times days\_admit^2 + \sum_m \beta_{area\_id_m} \times I(area\_id_m) + v\end{aligned}$$

where $\log(C_{IP})$ is a vector of log-transformed total cost reported for each inpatient discharge, with regressors from Table S1, and v is a vector of stochastic term independently distributed as $v \sim N(0, \sigma_v^2)$. The $\left(\beta_0,\ \{\beta_{PDX_j^{ICD-10}}\}_{j=2}^{140},\ \beta_{age},\ \cdots\ ,\ \{\beta_{area\_id_m}\}_m\right)$ are the inpatient cost regression parameters to be estimated. The $j,\ k,\ l$, and m denote the subscripts of dummy variables for ICD-10 Principal Diagnosis (PDx) code, service type, insurance type, and health service area of inpatient discharges. Therefore, the standardized cost for each inpatient case, $\hat{C}_{IP}$ could be obtained from the fitted regression model.

The estimations of average costs, $\hat{C}_{OP}$ and $\hat{C}_{IP}$, of medical treatment services are calculated separately by five hospital levels: primary, first-level secondary, second-level secondary, third-level secondary, and tertiary hospitals. The approach of separating cost regressions to compare means and other distributional moments is ordinary for applied econometric research. See Jones, Lomas, and Rice (2014, 2015) and Deng, Lou, and Mitsakakis (2019) as examples of separated regressions for medical costs.

The objective of this study focuses on the health workforce allocations. Thus, this study does not cover other production factors such as capital. It is arguably unpractical in terms of conceptualization to incorporate the capital component into the cost regression models. Nevertheless, this study indirectly reflects the capital factor by consolidating the hospital within the same or similar hospital levels.

Given that the unconditional mean of cost or $\bar{c}$ is approximately equal to the conditional mean predicted from the regression in numerical analysis, one can expect that the separate cost regressions provide different cost average levels according to the observed costs incurred within each hospital level. For instance, the higher-level hospitals tend to have higher cost averages than the lower-level hospitals. Similarly, this study separately standardizes the costs from OP and IP discharges, whereas the IP treatments tend to have higher average costs than the OP treatments. This is confirmed by the estimated constant coefficients of regression results in Tables S4-S5. We also need to separate the OP and IP regression models, because the OP treatment has no duration of admission, but the number of days admitted is an important feature of the IP treatment. Variations in the cost predictions reflect the heterogeneous attributes in each medical discharge at different hospital levels and whether OP or IP categories.

The reverse transformation for the theoretically consistent predictions of the logarithmic average costs is such that

$$\hat{C} = \exp\,(\log\,(\hat{C})) \times \exp\,(RMSE^2/2)$$

where $RMSE$ is the root mean squared error calculated from the differences between the standardized costs obtained by regression analysis and the reported costs from the health information system.[1]

Instead of counting each OP or IP case as the outputs for status quo and ex-ante scenarios, or equivalently assigning equal weights as ‘one’ for any discharges, this study uses the ‘relative labor cost’ weights to reflect the human resources expended for each OP and IP discharge. These weights are the estimated costs reflecting the observable characteristics of patient, service, hospital, and area for each OP or IP case. Therefore, the aggregated outputs reflect the economic values of health workforce resources used for each discharge. Tables S4-S5 at the end of this Supplementary Material report the regression results.

Reflecting labor cost component in the OP and IP costs

The estimated costs of OP and IP cases at each hospital level reflect both workloads of health workers and the other resources used. The original OP and IP costs calculated by the

[1] See theoretical discussion from pages 205-206 of Wooldridge, Jeffrey M. (2019). Introductory Econometrics: A Modern Approach. 7th edition. Cengage Learning.

Ministry of Public Health's hospitals come from the activity-based costing approach. This costing model considers both direct and indirect costs. The direct costs cover the labor, material, and capital costs, while the indirect costs are calculated as 20% of the total direct costs.

There is no information available on the labor cost of the reported OP and IP costs. Given microdata limitations, this study adjusted the estimated OP and IP costs with the hospital-level share of labor cost from the hospital financial statement in the same budget year of the OP and IP cases. This approach could help a better distinction between different workloads used in each OP or IP treatment instead of using the total costs that also cover other cost components. Thus, the quantified output in this study excludes material, capital, or another cost components. Table S2 reports the summary statistics of the share of labor cost from different hospital levels, in which this study assigns the hospital-level ratio of labor cost to each discharge.

Table S2: Summary statistics for share of labor cost

Hospital Levels	Mean	S.D.	Min	Max	N
Primary	64%	13%	26%	83%	9,609
First-level secondary	60%	7%	36%	76%	508
Mid-level secondary	55%	7%	35%	74%	264
High-level secondary	51%	7%	29%	68%	84
Tertiary	47%	6%	38%	58%	35

Source: Hospital-level trial balance sheet in the budget year 2019, Division of Health Economics and Health Security, MOPH

Workforce as inputs of public hospitals

Define $n_{i,j}$ as the number of health workforce in a public hospital i for health profession j such as medical doctor, nurse, dentist, pharmacist, and others. This study calculates relative weights for the workforce numbers of each profession by average work hours per week and average hourly earnings. Therefore, the hospital-level or area-based aggregations of the weighted numbers of health workers are the total worker valuation in monetary terms.

This study defines N_i as the total (weighted) workforce in hospital i, which N_i is an aggregation of total numbers of medical profession j multiplied with their relative weights calculated for economic costs:

$$N_i = \sum_j n_{i,j} * \overline{hour}_{public,j} * \overline{wage}_{public,j} = \sum_j n_{i,j} * weight_j$$

where, for any profession j, $\overline{hour}_{public,j}$ is the average work hours per week, and $\overline{wage}_{public,j}$ is the average hourly earnings. The weighted number of health professionals is subsequentially in monetary term reflecting economic costs of workforce.

This study calculates the average work hours per week and average earning per hour from the National Statistical Office's Labor Force Survey 2002Q1-2020Q1. The hourly earnings are temporally and spatially adjusted by deflators calculated from the official consumer price indexes at the regional level. Both average work hours per week and average hourly earnings are estimated with the regression models controlling for heterogeneity on sex, age, education, urban/rural areas, and regions for the health workers aged 15-64 in the public sector. The estimated work hours and hourly earnings for each medical profession are the regional averages and fixed at the budget year 2019 for the same period of the OP and IP cases and the health workforce in this study. The sample sizes are too small in several provinces, so this study uses the regional representation to envisage spatial heterogeneity.

Table S3 shows the averages of $\overline{hour}_{public,j}$ and $\overline{wage}_{public,j}$ in each region. The adjustment factors in the last column are the ratios between the multiplications of average work hours per week and average earning per hour, using the nurse profession in each region for the denominator as the base reference.

Table S3: Weights for public health workforce by profession

	$\overline{hour}_{public,j}$	$\overline{wage}_{public,j}$	$\overline{hour}_{public,j} \times \overline{wage}_{public,j}$	Adjustment Factor
Doctor				
Central	40.1	219.3	8,799.9	1.25
North	45.1	207.0	9,326.8	1.27
Northeast	45.3	192.9	8,743.7	1.22
South	48.1	224.6	10,809.6	1.55
Dentist				
Central	38.1	185.9	7,092.9	1.00
North	37.2	189.2	7,032.3	0.96
Northeast	39.2	178.1	6,976.7	0.97
South	38.9	184.2	7,173.1	1.03
Pharmacist				
Central	26.0	147.8	3,836.0	0.54
North	27.3	143.3	3,913.7	0.53
Northeast	27.7	139.2	3,855.6	0.54
South	27.0	152.1	4,106.7	0.59
Nurse				
Central	43.9	161.0	7,062.4	1.00
North	44.3	165.4	7,332.5	1.00
Northeast	45.6	157.3	7,177.9	1.00
South	44.2	158.1	6,985.8	1.00
Others				
Central	37.4	172.5	6,460.8	0.91
North	37.6	167.0	6,275.7	0.86
Northeast	38.6	159.2	6,151.5	0.86
South	39.2	161.1	6,309.6	0.90

Source: Labor Force Survey 2002Q1-2020Q1, National Statistical Office
Note: The estimated earnings and hours are fixed at the budget year 2019.
For each region, nurse is the base for weights of other medical professions.

Workload per worker measurement

The general concept for workload per worker is the output divided by input, which is

$$workload\ per\ worker = \frac{Output}{Input}$$

whereas the $Output$ is $\hat{y}_i = \widehat{OP}_i + \widehat{IP}_i$ which represents the weighted amount of medical treatment services delivered in the hospital i; and the $Input$, total weighted workforce used in health service delivery, is $N_i = \sum_j n_{i,j} * \overline{hour}_j * \overline{wage}_j = \sum_j n_{i,j} * weight_j$ for hospital i. Again, both output and input weights reveal economic costs in monetary terms.

Therefore, the equation for hospital workload per worker in this study is

$$workload\ per\ worker = \frac{\hat{y}_i}{N_i}$$

This analysis provides analytical results of comparing output per head before and after the area-based network consolidations at the different hospital and administrative area levels, i.e., comparing workload per worker between the status quo and ex-ante scenarios. The higher workload per worker in a public hospital does not necessarily imply higher productivity than others. However, it could exhibit the continuous problem of workforce scarcity in public hospitals.

Area-based network allocation

The counterfactual simulations of network consolidation quantify the area-based health workforce allocation within the local administrative areas. This study conducts simulations at different levels of hospital services: (a) all hospital levels altogether, (b) only within each hospital level, and (c) combining similar hospital levels. We can consider the area-based network of human resources as the gatekeeping system to optimize the system resources, given the demand for health care service and the workforce supply capacity.

The study hypothetically presumes that the network consolidations within the same administrative areas could enhance the health system's allocative efficiency by mitigating the workforce shortage. Figure S1 illustrates an example of area-based network allocation of four hospitals within the same administrative area. The existing status quo scenario postulates that the output $\hat{y}_i$ and the workers N_i are attached to only one hospital i. On the other hand, the ex-ante scenario combines the output and input from all n hospitals within the same area to optimize all feasible resources to reduce the supply- demand gap of human resources for health.

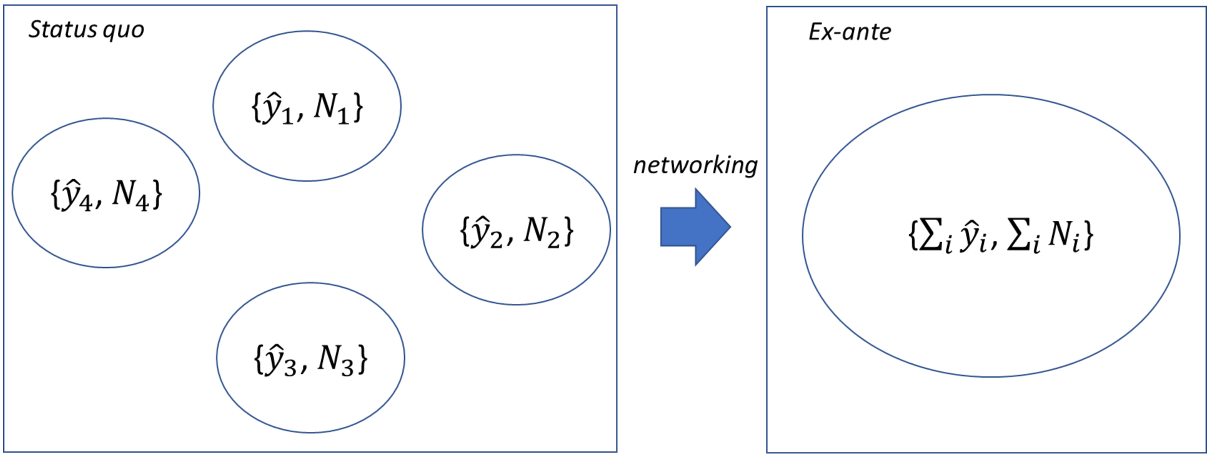


Figure S1. Example of a network of four hospitals within the same administrative area

Each hospital has the estimated quantities of $Output$ as $\hat{y}_i = \widehat{OP}_i + \widehat{IP}_i$ and $Input$ as $N_i = \sum_j n_{i,j} * \overline{hour}_{public,j} * \overline{wage}_{public,j} = \sum_j n_{i,j} * weight_j$ for hospital $i = 1,2,3,4.$

The status quo scenario of workload per worker is the average workload per worker of all four hospitals. This can be written as $\sum_{i=1}^{4} \frac{\hat{y}_i}{N_i}/4.$

The ex-ante scenario is the average workload per worker after consolidating all four hospitals altogether. This can be written as $\frac{\sum_{i=1}^{4} \hat{y}_i}{\sum_{i=1}^{4} N_i}.$

When all the $\hat{y}_i$ are normalized into the same unit of measurements, i.e., the unit of OP case in the primary hospitals, one can compare the average reduction in workload per worker as the percentage change between the status quo and ex-ante scenarios. For instance, it could be expressed as 1-[($\frac{\sum_{i=1}^{4}\hat{y}_i}{\sum_{i=1}^{4}N_i}$)/($\sum_{i=1}^{4}\frac{\hat{y}_i}{N_i}/4$)].

In general terminology, the status quo situation for the average workload per worker of n hospitals within a local administrative area can be expressed as the following:

$$\sum_{i=1}^{n}\frac{\frac{\hat{y}_i}{N_i}}{n}$$

On the other hand, the ex-ante situation for the average workload per worker after combining the output and input from all n hospitals within the area can be expressed as the following:

$$\frac{\sum_{i=1}^{n}\hat{y}_i}{\sum_{i=1}^{n}N_i}$$

Therefore, the average reduction in workload per worker of this area can expressed in a general form as the following:

$$1-\frac{\frac{\sum_{i=1}^{n}\hat{y}_i}{\sum_{i=1}^{n}N_i}}{\sum_{i=1}^{n}\frac{\hat{y}_i}{N_i}/n}$$

At the aggregated levels of administrative areas of interested, such as health service areas $m = 1,2,\cdots$, the average reduction in workload per worker from consolidating within each of the health service areas can be expressed as the following:

$$1-\frac{\sum_{m}\frac{\frac{\sum_{i_m=1}^{n_m}\hat{y}_{i_m}}{\sum_{i_m=1}^{n_m}N_{i_m}}}{m}}{\sum_{\substack{i_m=1\\ \forall m}}^{n_m}\frac{\hat{y}_{i_m}}{N_{i_m}}}$$

for i_m and n_m denoted the hospital i_m with a total of n_m hospitals in the health service area m. The nominator is the average *ex-ante* workload per worker across areas, while the denominator is simply the average *status quo* workload per worker of all hospitals from every health service area. Essentially, this formula is the comparison of the status quo and ex-ante quantities from consolidating across every health service area m.

This study applies the last formula for other administrative area levels such as sub-district, district, and province across categorical hospital levels such as all hospital levels, within the same hospital levels only, or similar hospital levels.

For standard measurement, this study normalizes the workload per worker to the identical measurement unit of primary-level OP discharge for comparability between outpatient and inpatient services across different hospital levels. This study obtains the national average cost of primary-level OP service from the fitted regression model at 108 Thai Baht. This average cost is multiplied by 0.64 as the national average share of labor cost in the primary hospitals. Consequentially, the total output of all public hospitals in this study is equivalent to the workloads of 1,204,133,398 OP cases at the primary-level hospitals.

Lastly, this study evaluates the economic value of each network consolidation option. The economic value is simply a multiplication of the number of the service delivery units, average workforce per service delivery unit, average OP cases per worker, the average reduction in OP cases per worker, and the average labor cost of the OP case. All these quantities, but the last one, are available from the result tables of area-based network allocation in the main manuscript. The average labor cost of the OP case is calculated from the primary hospitals discussed above.

Therefore, one can multiply the number of provinces with the average workforce per province, average OP cases per worker, average OP case reductions per worker, and the average labor cost of the OP case to calculate the economic value of the provincial-level consolidation. Similarly, one can conduct such network consolidation calculations of economic valuation for other levels of administrative areas and different categories of hospital levels.

Finally, we can obtain the estimated economic values associated with the network consolidation options such that we can evaluate the appropriate choices which are feasible for the system capabilities and aligned with the system development goals.

Regression results

Table S4: OLS regression of log of cost of outpatient treatments

Dependent variable: log-transformed total cost of outpatient discharge	**Primary**	**First-level secondary**	**Second-level secondary**	**Third-level secondary**	**Tertiary**
Age	-0.0000655***	0.00756***	0.00897***	0.0110***	0.0115***
	-4.39	263.64	229.21	213.04	233.40
Age squared	0.0000249***	-0.0000428***	-0.0000480***	-0.0000584***	-0.0000477***
	142.67	-133.47	-109.67	-101.57	-86.30
Female (relative to male)	-0.0230***	-0.0105***	-0.0217***	-0.0322***	-0.0550***
	-115.30	-29.72	-45.53	-54.73	-95.37
Out-office hours (relative to office hours)	0.00365***	0.0106***	0.0125***	0.0585***	0.0204***
	14.74	29.13	25.66	96.09	34.63
By appointment (relative to walk-in)	0.132***	0.202***	0.302***	0.322***	0.264***
	244.82	439.86	516.88	490.24	423.79
Refer from other hospital (relative to walk-in)	0.187***	0.395***	0.115***	0.347***	0.380***
	43.44	119.61	31.32	211.81	238.65
Refer from emergency service or EMS (relative to walk-in)	-0.0117*	0.149***	0.273***	-0.0765***	-0.325***
	-2.49	22.53	37.73	-7.74	-51.58
CSMBS (relative to UCS)	0.0576***	0.207***	0.205***	0.297***	0.248***
	135.21	390.80	290.54	387.17	320.63

Dependent variable: log-transformed total cost of outpatient discharge	**Primary**	**First-level secondary**	**Second-level secondary**	**Third-level secondary**	**Tertiary**
SSS (relative to UCS)	0.0268***	-0.0771***	-0.0642***	-0.0117***	-0.162***
	65.54	-108.46	-69.03	-12.55	-185.09
OOPE (relative to UCS)	0.0178***	-0.00994***	0.0386***	0.0608***	-0.0530***
	25.71	-12.05	38.20	48.89	-50.82
Health Service Area: 2 (relative to HSA 1)	0.190***	0.191***	0.197***	0.156***	1.495***
	354.45	230.32	145.58	109.72	870.94
Health Service Area: 3 (relative to HSA 1)	-0.00332***	-0.0173***	-0.136***	-0.271***	0.272***
	-6.64	-22.78	-69.90	-185.49	134.61
Health Service Area: 4 (relative to HSA 1)	-0.0589***	0.138***	0.0190***	-0.0232***	0.226***
	-121.33	149.80	17.75	-18.39	149.75
Health Service Area: 5 (relative to HSA 1)	-0.168***	0.125***	0.147***	0.0548***	0.164***
	-357.38	158.06	140.17	43.14	138.35
Health Service Area: 6 (relative to HSA 1)	0.0952***	0.137***	0.0797***	-0.439***	0.642***
	201.35	157.04	75.33	-210.32	557.00
Health Service Area: 7 (relative to HSA 1)	0.176***	0.125***	0.321***	0.0890***	0.271***
	416.72	176.06	269.12	57.45	196.03
Health Service Area: 8 (relative to HSA 1)	0.298***	-0.0218***	0.263***	-0.0597***	0.746***
	730.10	-29.41	187.89	-47.67	447.65
Health Service Area: 9 (relative to HSA 1)	0.0898***	0.0594***	0.113***	-0.419***	0.551***
	219.92	72.63	116.41	-201.59	443.56

Dependent variable: log-transformed total cost of outpatient discharge	**Primary**	**First-level secondary**	**Second-level secondary**	**Third-level secondary**	**Tertiary**
Health Service Area: 10 (relative to HSA 1)	0.0438***	0.713***	0.311***	0.140***	1.128***
	90.73	974.78	240.47	99.82	814.82
Health Service Area: 11 (relative to HSA 1)	0.0134***	0.171***	0.163***	0.125***	0.545***
	24.37	230.21	138.53	72.68	425.76
Health Service Area: 12 (relative to HSA 1)	0.0452***	0.0959***	0.133***	0.0257***	0.131***
	87.40	129.37	112.24	20.48	103.86
Constant	3.744***	4.814***	4.659***	5.076***	4.645***
	1120.16	1612.09	1171.51	1148.17	1109.25
Observations	116,382,110	53,351,160	29,338,847	22,611,176	30,149,270
R-squared	0.158	0.190	0.193	0.182	0.182

Note: The dummy variables for principle diagnostic codes of 140 disease categories are not shown.

* *P*<0.05, ** *P* <0.01, *** *P* <0.001 with *t*-statistics in the second row.

Table S5: OLS regression of log of cost of inpatient treatments

Dependent variable: log-transformed total cost of inpatient discharge	**Primary**	**First-level secondary**	**Second-level secondary**	**Third-level secondary**	**Tertiary**
Age	0.00361 1.91	0.00217*** 14.63	0.00552*** 36.74	0.0141*** 66.54	0.0150*** 95.29
Age squared	-0.0000294 -1.45	-0.000000992 -0.62	-0.0000148*** -9.03	-0.0000909*** -39.25	-0.000135*** -79.57
Female (relative to male)	-0.0972*** -3.49	-0.0393*** -19.51	-0.0609*** -29.49	-0.0890*** -32.01	-0.0691*** -34.06
Out-office hours (relative to office hours)	-0.108*** -3.76	-0.0387*** -19.69	-0.0404*** -20.13	-0.334*** -125.92	-0.133*** -68.67
By appointment (relative to walk-in)	0.172** 2.98	-0.182*** -47.04	0.0632*** 18.31	-0.188*** -43.79	0.230*** 83.63
Refer from other hospital (relative to walk-in)	-0.537*** -5.85	-0.0334*** -4.20	-0.131*** -23.18	0.364*** 102.43	0.867*** 348.80
Refer from emergency service or EMS (relative to walk-in)	0.315*** 5.34	-0.0698*** -9.01	0.0682*** 7.85	-0.232*** -20.39	0.394*** 55.34
CSMBS (relative to UCS)	0.326*** 6.17	0.0485*** 13.43	-0.00319 -0.92	0.235*** 54.17	0.160*** 51.09
SSS (relative to UCS)	0.312***	0.0311***	0.0567***	0.209***	-0.0777***

Dependent variable: log-transformed total cost of inpatient discharge	**Primary**	**First-level secondary**	**Second-level secondary**	**Third-level secondary**	**Tertiary**
	4.17	6.01	11.67	36.54	-20.47
OOPE (relative to UCS)	-0.0959	0.280***	0.129***	0.241***	-0.756***
	-0.88	49.12	26.71	41.38	-214.33
Days admitted	0.00747	0.0475***	0.00925***	0.0160***	0.0479***
	0.67	89.77	24.54	60.34	163.15
Days admitted squared	0.000107	-0.000253***	-0.0000822***	-0.0000714***	-0.000172***
	0.16	-23.17	-11.04	-26.99	-52.47
Health Service Area: 2 (relative to HSA 1)		1.276***	-0.0348***	0.335***	1.456***
		198.17	-6.57	45.08	306.84
Health Service Area: 3 (relative to HSA 1)		-0.0558***	1.981***	-2.325***	-3.165***
		-13.87	216.35	-418.11	-998.85
Health Service Area: 4 (relative to HSA 1)		0.0164***	0.111***	-0.823***	0.612***
		3.65	23.51	-124.08	98.87
Health Service Area: 5 (relative to HSA 1)		-0.0519***	0.168***	-0.556***	-2.157***
		-11.23	37.70	-82.30	-669.38
Health Service Area: 6 (relative to HSA 1)	-0.587***	0.687***	0.0298***	-1.938***	-0.304***
	-13.60	106.10	6.72	-306.22	-75.98
Health Service Area: 7 (relative to HSA 1)		-0.0715***	0.341***	-1.218***	-1.929***
		-19.40	68.57	-176.73	-537.22

Dependent variable: log-transformed total cost of inpatient discharge	**Primary**	**First-level secondary**	**Second-level secondary**	**Third-level secondary**	**Tertiary**
Health Service Area: 8 (relative to HSA 1)	-1.004***	0.126***	0.434***	-1.297***	-0.572***
	-22.44	-13.87	216.35	-418.11	-998.85
Health Service Area: 9 (relative to HSA 1)		-0.0432***	0.306***	-1.838***	-1.210***
		-10.01	79.99	-215.43	-399.01
Health Service Area: 10 (relative to HSA 1)		2.245***	-0.419***	-2.462***	1.188***
		520.69	-103.04	-407.56	284.75
Health Service Area: 11 (relative to HSA 1)	-1.312	0.620***	0.258***	0.818***	-0.756***
	-1.19	3.65	23.51	-124.08	98.87
Health Service Area: 12 (relative to HSA 1)		-0.0402***	0.515***	-0.438***	-2.557***
		-9.35	96.25	-62.97	-655.52
Constant	4.254***	4.401***	4.246***	5.793***	6.284***
	14.74	-11.23	37.70	-82.30	-669.38
Observations	4,366	3,006,332	1,886,323	2,250,352	4,456,539
R-squared	0.172	0.214	0.099	0.195	0.331

Note: The dummy variables for principle diagnostic codes of 140 disease categories are not shown.

* *P*<0.05, ** *P* <0.01, *** *P* <0.001 with *t*-statistics in the second row.