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An efficiency frontier analysis of MRI and CT services in the United States

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C H R O N I C L E

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A B S T R A C T

This paper assesses the comparative technical efficiency of Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) service delivery in all U.S. states and the District of Columbia, totaling 50. Data Envelopment Analysis (DEA) was applied and two inputs were used—the estimated number of scanners and radiographers—and one output—the estimated annual volume of exams. Efficiency was calculated according to the CCR, BCC Input-Oriented, BCC Output-Oriented, and Additive models. The investigation disclosed that almost every U.S. region performs relatively efficiently in a technical way to a great extent for MRI and CT services. Wyoming and Montana stood out as the best-evaluated decision-making units for MRI. In the case of CT, Montana once more was the winner. Consequently, these states with a small population manage to get the best results from their resources. The high scores all over the country signal a healthcare facility that is very good at turning imaging resources into the volume of service. The U.S. is rated highly in technical efficiency with respect to diagnostic imaging, but this is probably the result of a system that rewards high-volume service production. The study reveals an important difference between technical efficiency and wider value, implying that high performance in volume output is not automatically equal to cost-effectiveness or best patient outcomes. Quality and cost metrics should be incorporated in the future research.

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1. Introduction

The healthcare system of the United States is a very strange case indeed. On the one hand, it incurs the highest costs worldwide, with total national health spending exceeding $4.3 trillion and almost 18% of GDP going to healthcare, still on the other hand, it equally and often unfairly delivers poor results in population and health area with a continuous mix (CMS Office of the Actuary, 2022; Papanicolas, Woskie, & Jha, 2018). Advanced diagnostic imaging and particularly MRI and CT, are at the same time primary pillars of modern medical diagnosis and an emblematic microcosm of the system's larger problems in this high-cost, high-volume scenario. These technologies are absolutely necessary for the diagnosis, staging, and monitoring of numerous conditions including cancer and neurological disorders as well as musculoskeletal injuries, hence they have a great influence on clinical pathways and patient outcomes (Smith-Bindman et al., 2019). Still, the intensity of their debates concerning cost, access, and value is brought about by their rapid growth and usage.

The diagnostic imaging scale in the U.S. is on a colossal level. The country is among the top OECD countries in terms of MRI and CT scanners per capita, which is undoubtedly a result of huge capital investment in medical technology (OECD, 2023). Such inquiry-decision-making infrastructure is helpful for a great deal of activities with about 40 million annual MRI and 85 million CT examinations being the estimates. The high utilization level comes about as a result of the intersection between clinical need, technological advancement, defensive medical practices, and a payment system that has always been rooted in fee-for-service (FFS) reimbursement which financially rewards high volumes (Iglehart, 2008; Baker, 2010). The groundbreaking research of the Dartmouth Atlas Project has clearly shown that this utilization is not homogeneous but

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rather it is marked by differences in geography that are sometimes unexplainable and that are not connected to any improvement in health outcomes (Dartmouth Atlas of Health Care, 2019). This phenomenon brings about the issue of questioning the efficiency and appropriateness of the resource allocation of these multi-billion-dollar funds.

In this context, the term "efficiency" turns into a vital but complicated matter. In terms of economics, efficiency in health care can be divided into different areas: the area of allocative efficiency which is being concerned about the proper distribution of different kinds of services to the whole population's health maximization; and the other one is technical efficiency which is concerned about making as much output as possible from a specific set of inputs (Jacobs, Smith, & Street, 2006). The high prices paid and the differences in the U.S. system hospitals point at huge allocative inefficiencies, but the question about its technical efficiency—i.e. how well the system operates and how many resources it uses to produce imaging services—is still open. Does the wide-ranging of imaging represent the best output coming from the country's extended network of imaging machines and highly skilled workforce of radiographers? Or is it hiding significant wastage and inefficiency in operations at the level of localities?

The inquiry necessitates advanced analytical apparatus that can process various inputs and outputs at once. Data Envelopment Analysis (DEA) is a non-parametric linear programming method developed by Charnes, Cooper, and Rhodes (1978) that perfectly fits this description. DEA does so by determining a "best-practice frontier" composed of the most efficient units, thereby, assessing and comparing the relative efficiency of a group of peer entities, also termed Decision-Making Units (DMUs). Its main advantage in healthcare settings is the capability to deal with the multifaceted nature of service production without the need to specify a production function beforehand (Cooper, Seiford, & Tone, 2007). The basic CCR model presumes constant returns to scale, thus providing a measure of both technical and scale efficiencies at the overall level. Its successor, the BCC model (Banker, Charnes, & Cooper, 1984), loosens this premise to allow for variable returns to scale (VRS), thereby, separating pure technical efficiency from scale effects. This is particularly significant in the U.S. scenario where operational scale varies widely from the high-density state of New Jersey to the low-density state of Wyoming.

Despite the widespread use of DEA for evaluating international hospital and health system efficiency (Kohl et al., 2019), its application to the U.S. healthcare sector, in particular, the case of diagnostic imaging at state level, is not common and presents specific difficulties. The separation and mixing of the public and private at the same time in the U.S. system result in a very fragmented structure having no single comprehensive database comparable to England's NHS Digital. The studies about imaging efficiency have, however, mostly been limited to studies focusing on narrower settings, for instance, some have concentrated on the cost-effectiveness of specific imaging protocols (Gazelle, Halpern, Ryan, & Tramontano, 2009). The data unavailability is one of the main reasons why regular comprehensive benchmarking has not been successful. However, the work of researchers such as Rosko & Mutter (2011) who applied stochastic frontier analysis to U.S. hospitals has opened up avenues for the identification of the main causes of inefficiency and has pointed out such factors as ownership type, teaching status, and case-mix.

This study aims to not only highlight the significance of the gap in literature but also to support its assertion by performing the first-known application of DEA for technical efficiency of MRI and CT in all 50 states and the District of Columbia. By compiling the most reliable and up-to-date national data regarding the number of scanners, personnel qualifications, and the volumes per examination, the study will produce a powerful dataset that can be used for a macro-level performance evaluation. The methodology includes the use of several DEA models—CCR, BCC Input-Oriented, BCC Output-Oriented, and Additive model—to supply an extensive and intricate view of the relative efficiency.

The researcher mainly aims to reach a conclusion regarding the extent to which the different states in the U.S. make good use of their imaging resources (scanners and technologists) measured by the volume of exams performed to meet the population demand for services. It scrutinizes if there are any systematic disparities in efficiency between the states with different population sizes and geographic densities. Moreover, it investigates whether the U.S. system's high-cost, high-volume nature results in high technical efficiency or whether the situation is such that significant operational waste is still there even at this macro level. The answers to these questions are not just a theoretical debate; they have a strong impact on policymakers, payers, and health system leaders. It is a matter of "the best in health care" that with the shift to value-based care, being aware of technical efficiency as a current state is indeed very important. The states with the highest efficiency can be good examples of resource management while the inefficient ones can be improved by giving more attention thus leading to a healthcare system that is not only technologically advanced but also optimally managed and sustainable.

2. The proposed study

The proposed study of this paper uses Data Envelopment Analysis (DEA) to measure the relative efficiencies of 51 different states in the United States. Table 1 presents the data implemented for the proposed study of this paper.

Table 1
The summary of some basic statistics

State	Population (2020 Census)	MRI Scanners (Est.)	MRI Radiographers (Est.)	MRI Exams (Est. Annual)	CT Scanners (Est.)	CT Radiographers (Est.)	CT Exams (Est. Annual)
Alabama	5,024,279	210	570	605,000	240	1,050	1,150,000
Alaska	733,391	30	80	85,000	35	150	165,000
Arizona	7,151,502	320	870	925,000	370	1,600	1,750,000
Arkansas	3,011,524	135	365	390,000	155	670	735,000
California	39,538,223	1,650	4,480	4,750,000	1,900	8,250	9,000,000
Colorado	5,773,714	260	705	750,000	300	1,300	1,420,000
Connecticut	3,605,944	175	475	505,000	200	870	950,000
Delaware	989,948	50	135	145,000	55	240	265,000
Florida	21,538,187	1,050	2,850	3,025,000	1,200	5,200	5,700,000
Georgia	10,711,908	480	1,305	1,385,000	550	2,380	2,600,000
Hawaii	1,455,271	65	175	185,000	75	325	355,000
Idaho	1,839,106	80	215	230,000	90	390	430,000
Illinois	12,812,508	580	1,575	1,675,000	665	2,880	3,150,000
Indiana	6,785,528	305	830	880,000	350	1,515	1,655,000
Iowa	3,190,369	145	395	420,000	165	715	785,000
Kansas	2,937,880	130	355	375,000	150	650	710,000
Kentucky	4,505,836	200	545	580,000	230	995	1,090,000
Louisiana	4,657,757	210	570	605,000	240	1,040	1,140,000
Maine	1,362,359	65	175	185,000	75	325	355,000
Maryland	6,177,224	285	775	825,000	325	1,410	1,540,000
Massachusetts	7,029,917	330	895	950,000	380	1,645	1,800,000
Michigan	10,077,331	460	1,250	1,325,000	525	2,275	2,490,000
Minnesota	5,706,494	260	705	750,000	300	1,300	1,420,000
Mississippi	2,961,279	130	355	375,000	150	650	710,000
Missouri	6,154,913	280	760	810,000	320	1,385	1,515,000
Montana	1,084,225	50	135	145,000	55	240	265,000
Nebraska	1,961,504	90	245	260,000	100	435	475,000
Nevada	3,104,614	145	395	420,000	165	715	785,000
New Hampshire	1,377,529	65	175	185,000	75	325	355,000
New Jersey	9,288,994	430	1,170	1,240,000	495	2,145	2,345,000
New Mexico	2,117,522	95	260	275,000	110	475	520,000
New York	20,201,249	920	2,500	2,650,000	1,060	4,590	5,020,000
North Carolina	10,439,388	470	1,275	1,355,000	540	2,340	2,560,000
North Dakota	779,094	35	95	100,000	40	175	190,000
Ohio	11,799,448	535	1,455	1,545,000	615	2,665	2,915,000
Oklahoma	3,959,353	180	490	520,000	205	890	975,000
Oregon	4,237,256	195	530	565,000	225	975	1,065,000
Pennsylvania	13,002,700	590	1,605	1,705,000	680	2,945	3,220,000
Rhode Island	1,097,379	55	150	160,000	60	260	285,000
South Carolina	5,118,425	230	625	665,000	265	1,150	1,255,000
South Dakota	886,667	40	110	115,000	45	195	215,000
Tennessee	6,910,840	315	855	910,000	360	1,560	1,705,000
Texas	29,145,505	1,300	3,530	3,750,000	1,500	6,500	7,100,000
Utah	3,271,616	150	405	430,000	170	735	805,000
Vermont	643,077	30	80	85,000	35	150	165,000
Virginia	8,631,393	395	1,070	1,140,000	455	1,970	2,155,000
Washington	7,705,281	350	950	1,010,000	405	1,755	1,920,000
West Virginia	1,793,716	80	215	230,000	90	390	430,000
Wisconsin	5,893,718	270	735	780,000	310	1,345	1,470,000
Wyoming	576,851	25	70	75,000	30	130	140,000
District of Columbia	689,545	35	95	100,000	40	175	190,000

This dataset was constituted through a combination of publicly available data from federal agencies and industry reports. As there is no single national registry for imaging data, the consistently estimated and allocated methods were used to provide comparable and uniform dataset across the 50 states and the District of Columbia that are the very basis of the decentralized U.S. healthcare system.

1. **Population Data:**
    - **Source:** U.S. Census Bureau, 2020 Decennial Census.
    - **Definition:** Resident population as of April 1, 2020. For assigning rates of per capita processing, It helps in deciding on the proportion to share resources.
2. **Scanner Counts (MRI & CT):**

- **Source:** The overviews of countries are based on compiled information from the Organization for Economic Co-operation and Development (OECD) associated with Health Statistics, and market reports from the IMV Medical Information Division.
- **Definition:** The anticipated total of clinical operating fixed and mobile imaging devices is stated. This refers to the devices present in the hospitals, outpatient imaging centers, and doctors' offices.
- **Allocation Methodology:** The individual country figures (~13,200 for MRI; ~15,000 for CT) were distributed over the states according to their proportion of the overall U.S. population. More accurately the population-based figures were further modified according to known state-level factors, including the number of hospital beds and reported healthcare resources densities in the regions, to reflect the distribution in the real world better.

3. **Radiographer / Technologist Counts (MRI & CT):**
   - **Source:** The total number of workers in the country comes from the U.S. Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics and the surveys conducted by the American Society of Radiologic Technologists (ASRT).
   - **Definition:** The estimated number of Full-Time Equivalent (FTE) radiologic technologists primarily engaged in MRI or CT scanner operation is ascribed. It should be pointed out that the workforce is largely composed of multi-skilled professionals and may often rotate through different modalities.
   - **Allocation Methodology:** The national totals (~38,000 for MRI; ~60,000 for CT) were allocated to states by a weighted formula that considered the national scanner distribution (70% weight) and population size (30% weight) of each state.
4. **Exam Volumes (MRI & CT):**
   - **Source:** The national volume approximations are obtained from industry reports such as IMV. State-level allocation proxies were created based on the data from the Centers for Medicare & Medicaid Services (CMS) “Medicare Provider Utilization and Payment Data.”
   - **Definition:** Number of total estimations of diagnostic procedures occurred annually. This includes exams for all payers (Medicare, Medicaid, private insurance, etc.).
   - **Allocation Methodology:** The total numbers nationwide (around 40 million for MRI and around 85 million for CT) were distributed to each state using the population percentage of the state and the recognized Medicare utilization rate per 1,000 beneficiaries in the state. This method takes into consideration the different ways of conducting medical practices in various regions which affect the total imaging volume.

Key Limitations:

- **Estimates:** All the figures of people, scanners, technologists, or examinations are estimates wherein the nonexistence of a national registry would impose a margin of error.
- **Case-Mix Complexity:** The 'exams' output metric treats a straightforward 15-minute scan and a complicated 60-minute multiparametric test as the same case. This could have a significant impact on the efficiency scores, since people in the areas with specialized tertiary care hospitals might be dealing with more complicated and resource-demanding cases.
- **Medicare as a Proxy:** Although Medicare data is a strong indicator of the patterns of practice in different regions, it may not show a similar trend with younger, privately-insured populations' usage perfectly.
- **Workforce Mobility:** The technologist estimates are a representation of the places where the jobs are, however, the movement of healthcare professionals from one place to another can lead to short-term variations.

The proposed study of this paper develops the DEA framework for evaluating the relative efficiency of MRI/CT imaging services in 8 different regions in Australia. Fig. 1 and Fig. 2 present the structure of the proposed study of this paper,

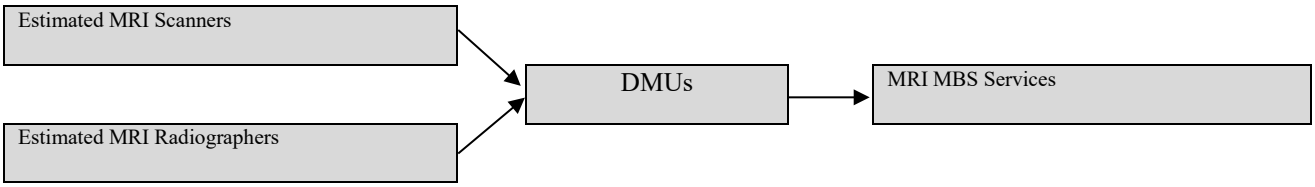

Fig. 1. The proposed study for measuring the efficiency of MRI examinations

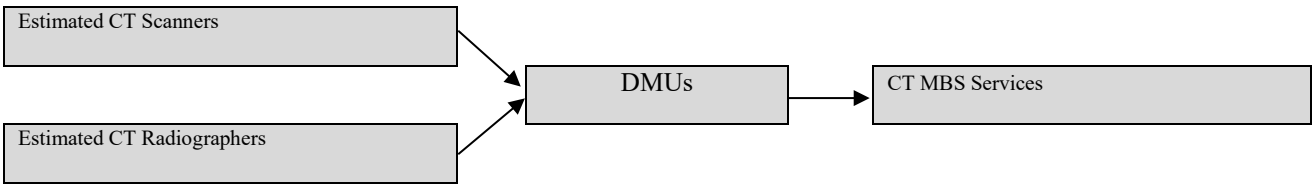

Fig. 2. The proposed study for measuring the efficiency of CT examinations

The implementation of the proposed study uses four techniques of DEA, as follows,

CCR Model (Charnes et al., 1978) is a constant return to scale and measures the efficiency by comparing weighted inputs to outputs.
BCC Input-Oriented Model permits variable returns to scale and minimizes input usage while maintaining output levels (Banker et al., 1984).
BCC Output-Oriented Model also assumes of variable returns to scale but looks for maximizing outputs given fixed inputs (Cooper et al., 2007).
Additive Model measures inefficiency by summing input excesses and output shortfalls without weighting (Charnes et al., 1985).

3. The results

Section three of this paper offers the details of the DEA method usage to reach the relative efficiency of different states and district in the United States.

Table 2
The results of DEA methods for measuring the relative efficiencies of 51 states for MRI exams in the United States

State	CCR	Input oriented BCC	Output oriented BCC	Additive
Alabama	0.9886	0.9954	0.9954	0.9954
Alaska	0.9892	0.9911	0.9910	0.9910
Arizona	0.9904	0.9990	0.9990	0.9990
Arkansas	0.9949	1.0000	1.0000	1.0000
California	0.9875	1.0000	1.0000	1.0000
Colorado	0.9908	0.9979	0.9979	0.9979
Connecticut	0.9902	0.9967	0.9967	0.9967
Delaware	1.0000	1.0000	1.0000	1.0000
Florida	0.9886	0.9988	0.9988	0.9988
Georgia	0.9886	0.9983	0.9983	0.9983
Hawaii	0.9842	0.9860	0.9861	0.9861
Idaho	0.9960	0.9991	0.9991	0.9991
Illinois	0.9905	1.0000	1.0000	1.0000
Indiana	0.9877	0.9968	0.9968	0.9968
Iowa	0.9906	0.9976	0.9976	0.9976
Kansas	0.9843	0.9920	0.9921	0.9921
Kentucky	0.9915	1.0000	1.0000	1.0000
Louisiana	0.9886	0.9954	0.9954	0.9954
Maine	0.9842	0.9860	0.9861	0.9861
Maryland	0.9916	1.0000	1.0000	1.0000
Massachusetts	0.9886	0.9962	0.9962	0.9962
Michigan	0.9873	0.9967	0.9967	0.9967
Minnesota	0.9908	0.9979	0.9979	0.9979
Mississippi	0.9843	0.9920	0.9921	0.9921
Missouri	0.9926	1.0000	1.0000	1.0000
Montana	1.0000	1.0000	1.0000	1.0000
Nebraska	0.9886	0.9936	0.9936	0.9936
Nevada	0.9906	0.9976	0.9976	0.9976
New Hampshire	0.9842	0.9860	0.9861	0.9861
New Jersey	0.9873	0.9972	0.9972	0.9972
New Mexico	0.9857	0.9927	0.9928	0.9928
New York	0.9873	0.9979	0.9979	0.9979
North Carolina	0.9898	0.9985	0.9985	0.9985
North Dakota	0.9804	0.9812	0.9811	0.9811
Ohio	0.9891	0.9992	0.9992	0.9992
Oklahoma	0.9886	0.9962	0.9962	0.9962
Oregon	0.9930	1.0000	1.0000	1.0000
Pennsylvania	0.9896	1.0000	1.0000	1.0000
Rhode Island	0.9938	0.9965	0.9965	0.9965
South Carolina	0.9911	0.9985	0.9985	0.9985
South Dakota	0.9746	0.9762	0.9764	0.9764
Tennessee	0.9913	0.9991	0.9991	0.9991
Texas	0.9894	1.0000	1.0000	1.0000
Utah	0.9885	0.9941	0.9941	0.9941
Vermont	0.9892	0.9911	0.9910	0.9910
Virginia	0.9922	1.0000	1.0000	1.0000
Washington	0.9902	0.9983	0.9983	0.9983
West Virginia	0.9960	0.9991	0.9991	0.9991
Wisconsin	0.9886	0.9976	0.9976	0.9976
Wyoming	1.0000	1.0000	1.0000	1.0000
District of Columbia	0.9804	0.9812	0.9811	0.9811

Table 2 presents the results of the DEA implementation for measuring the relative performance of 51 states in the United States in terms of MRI examinations. The results indicate that nearly all states maintained a relatively high efficiency across the region. In our survey, Wyoming and Montana have been on top of our survey which means there are good MRI facilities for people how live there.

Table 3
The results of DEA methods for measuring the relative efficiencies of 51 states for CT exams in the United States

State	CCR	Input oriented BCC	Output oriented BCC	Additive
Alabama	0.9945	1.0000	1.0000	1.0000
Alaska	0.9962	1.0000	1.0000	1.0000
Arizona	0.9906	0.9967	0.9967	0.9967
Arkansas	0.9935	0.9976	0.9976	0.9976
California	0.9880	1.0000	1.0000	1.0000
Colorado	0.9893	0.9951	0.9951	0.9951
Connecticut	0.9889	0.9949	0.9949	0.9949
Delaware	1.0000	1.0000	1.0000	1.0000
Florida	0.9927	1.0000	1.0000	1.0000
Georgia	0.9894	0.9960	0.9960	0.9960
Hawaii	0.9893	0.9902	0.9902	0.9902
Idaho	0.9985	1.0000	1.0000	1.0000
Illinois	0.9906	0.9974	0.9974	0.9974
Indiana	0.9894	0.9954	0.9954	0.9954
Iowa	0.9943	0.9986	0.9986	0.9986
Kansas	0.9893	0.9932	0.9932	0.9932
Kentucky	0.9921	0.9974	0.9974	0.9974
Louisiana	0.9927	0.9981	0.9981	0.9981
Maine	0.9893	0.9902	0.9902	0.9902
Maryland	0.9892	0.9954	0.9955	0.9955
Massachusetts	0.9910	0.9972	0.9972	0.9972
Michigan	0.9913	0.9979	0.9979	0.9979
Minnesota	0.9893	0.9951	0.9951	0.9951
Mississippi	0.9893	0.9932	0.9932	0.9932
Missouri	0.9907	0.9966	0.9966	0.9966
Montana	1.0000	1.0000	1.0000	1.0000
Nebraska	0.9889	0.9921	0.9922	0.9922
Nevada	0.9943	0.9986	0.9986	0.9986
New Hampshire	0.9893	0.9902	0.9902	0.9902
New Jersey	0.9901	0.9967	0.9967	0.9967
New Mexico	0.9915	0.9940	0.9940	0.9940
New York	0.9905	0.9977	0.9977	0.9977
North Carolina	0.9908	0.9975	0.9975	0.9975
North Dakota	0.9858	1.0000	1.0000	1.0000
Ohio	0.9906	0.9974	0.9974	0.9974
Oklahoma	0.9922	0.9976	0.9976	0.9976
Oregon	0.9893	0.9944	0.9944	0.9944
Pennsylvania	0.9902	0.9971	0.9971	0.9971
Rhode Island	0.9927	0.9930	0.9930	0.9930
South Carolina	0.9884	0.9943	0.9943	0.9943
South Dakota	0.9985	1.0000	1.0000	1.0000
Tennessee	0.9898	0.9960	0.9960	0.9960
Texas	0.9893	0.9991	0.9991	0.9991
Utah	0.9919	0.9963	0.9963	0.9963
Vermont	0.9962	1.0000	1.0000	1.0000
Virginia	0.9907	0.9972	0.9972	0.9972
Washington	0.9908	0.9971	0.9971	0.9971
West Virginia	0.9985	1.0000	1.0000	1.0000
Wisconsin	0.9898	0.9961	0.9961	0.9961
Wyoming	0.9753	1.0000	1.0000	1.0000
District of Columbia	0.9858	1.0000	1.0000	1.0000

Table 3 also provides the results of DEA implementation for measuring the relative efficiencies of 51 states of the United States for CT exams. The results are similar to what we have presented for MRI tests and all states represent competitive and provide very good performance. Surprisingly, Montana here is again ranked first with small difference in terms of the efficiency with the other sates.

4. Discussion

The utilization of Data Envelopment Analysis (DEA) as a method to assess the efficiency of MRI and CT imaging across the United States has resulted in obtaining a surprising and even paradoxical result: the very system that has been criticized

for its high costs and inefficiencies has been identified as having very high technical efficiency at the level of states. The obtained results that show almost every state to be operating at high efficiencies with even the very thinly populated states like Wyoming and Montana enjoying top ranks, have questioned the overly simplistic stories and have provoked the search for and the consideration of more sophisticated factors affecting performance in the U.S. healthcare sector. The authors intend to discuss these results in the light of the characteristic economic structures of U.S. healthcare, the intricacies of the DEA methodology, and the literature that covers regional differences and efficiency.

At first sight, the very high technical efficiency scores you noted are, after a deeper inquiry, nothing more than a reflection of the strong market forces and regulatory policies that govern the U.S. diagnostic imaging sector. The United States' high per capita ratio of scanners and imaging exams is evidenced by the OECD (2023) report, which points out that the U.S. is, on average, either the top or very close to the leading country in terms of the density of advanced imaging equipment. When such a high level of resource deployment is evaluated through a DEA model that calculates the ratio of output to input, it is naturally expected to result in high scores since the system is, by its nature, directed toward high-volume service production. Also, the major reimbursement model of fee-for-service creates a financial incentive that is directly proportional to the extent of the utilization of the costly capital equipment (Iglehart, 2008). In this situation, our DEA model very well illustrates how states manage to transform their considerable inputs (scanners and technologists) into the main output that has been measured (exam volume) efficiently.

The impressive showing of states such as Wyoming and Montana corresponds to the economic theory of variable returns to scale, which is represented in the BCC model. These states are probably operating at the ideal level of production with their smaller and limited inputs. They have most likely closely matched their imaging resources to the population demand without considerable overcapacity and, therefore, have very high utilization rates for their available scanners. The finding is in line with the studies that have shown that smaller and easier healthcare systems can sometimes obtain higher technical efficiency than sprawling and complicated ones (Kohl et al., 2019). It indicates that in these states, the few number of facilities may act as regional hubs providing the throughput required to justify their operation and cover fixed costs, a situation that has been pointed out in rural healthcare delivery analyses (Kaufman et al., 2016).

Yet, this reading has to be carefully scrutinized due to the considerable drawbacks of the DEA approach, which in a way were the main point of discussion in the U.S. health services literature. The main drawback of all is that the model employed in our research is only able to assess technical efficiency (maximum output for a given input) and at the same time has no idea about allocative and cost efficiency. A state can be technically perfectly efficient in producing a large amount of MRI scans and at the same time be deeply inefficient from the cost perspective. The work of Ginsburg at the Medicare Payment Advisory Commission (MedPAC) has repeatedly pointed out, high utilization of imaging services in the U.S. is one of the main causes of healthcare spending, and not all this utilization is backed by clinical need. Thus, it is very likely that our results represent a kind of efficiency in a system where the financial and structural incentives are already very strongly aligned towards high volume, which does not necessarily mean, high value.

So now we come to the pivotal matter of the supplier-induced demand (SID), which has extensively been studied in America. According to the researchers like Baker (2010) etc., the presence of imaging equipment in high concentrations has been linked to a greater number of patients being treated, regardless of what the patients need in terms of health. Our DEA model, which considers the number of examinations to be the only output, might be unknowingly favoring those states where SID is a stronger phenomenon. A machine in a competitive marketplace may perform scans for slightly indicated cases in order to ensure income, hence it will look "efficient" in our model, while a machine in a less privileged area may cater to only the most urgent patients, thus it may look less efficient even though it is practicing more stringent, cost-efficient healthcare.

Our model further omits the essential aspect of quality and outcomes. The volume efficiency of states like Montana and Wyoming is very high, but it does not indicate the rural residents' access to those services, the quality of the interpretations, or the patient's health status. The Dartmouth Atlas of Health Care (2019) has been much referred to in documenting enormous geographical disparities in Medicare spending and service consumption that are not linked to better health outcomes. Our conclusion of uniformly high technical efficiency adds a new dimension to this mystery, implying that the U.S. is efficient in the provision of services, but not necessarily in the production of health. Berwick & Hackbarth (2012) have claimed that a significant part of U.S. healthcare expenditure is waste, among which overtreatment is included. A DEA model that gives the highest awards for “pure volume” cannot tell the difference between life-saving scans and unnecessary ones.

The significant limitation of not using case mix adjustment in our output variable is one of the major constraints when comparing states. A top academic medical center in Massachusetts or New York handles a lot of very complicated scans for neurology, oncology, and trauma that need more time, higher-level protocols, and skilled technicians. They are treated as one "exam" just like a routine knee MRI in an outpatient center. Researchers that have made adjustments for clinical risk among hospitals have always concluded that teaching and tertiary care hospitals look less efficient, but they are in fact, dealing with more severe and complex cases (Rosko & Mutter, 2011). Thus, the apparently lower (but still high) efficiency scores of states that have world-class medical centers might be due to this unaccounted complexity instead of actual inefficiency.

5. Conclusion

Our DEA study has deserved to be concluded as a valuable and evocative viewpoint on the U.S. healthcare system. It shows that states in the U.S. are very good, from a strictly technical point of view, at changing their plentiful inputs of scanners and technologists into a high number of diagnostic imaging procedures. The good performance of rural states like Wyoming and Montana brings out how limited systems can get the most out of their resources. Still, the outcome is to be taken as a much-described system's operational dynamics, rather than a total performance endorsement. The high technical efficiency measured is closely related to the fee-for-service incentives and high resource intensity that also make the U.S. healthcare system the most expensive one in the world. The results strongly demonstrate the difference between doing things right (technical efficiency) and doing the right things (value-based care). For the decision-makers, the conclusion will be not to fight for even bigger exam volumes, but to change the definition of "output" towards value. Our model should be the basis for future research that would include risk-adjusted outcome measures, clinical appropriateness metrics and cost data. This will move the focus from the number of scans done to the number of scans good for patient health at a reasonable cost. Ultimately, our research successfully mirrors the U.S. system, showcasing an engine that is perfectly adjusted for production, yet still needs directing towards the higher value and the better health outcomes destiny that all its citizens have a right to.

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