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Exploring relationships between medical college rankings and performance with big data

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Abstract

Background: It is important to examine the cost-effectiveness of medical education. The public wants to know how government spending is being utilized to train doctors. There are very few studies that examine national data to understand the relationships between medical education and outcomes.
We used Big Data analytics with open health data to explore answers. We joined physician data and hospital total performance score data reported by Center for Medicare and Medicaid Services (CMS), containing information for nearly 600,000 practitioners and performance scores from three thousand hospitals in the United States. We combined this data medical college costs from the American Association of Medical Colleges and medical school rankings. We used Mullan's social mission to compare medical schools. We also computed the correlation between the rankings of 4-year baccalaureate colleges in the US published by the Wall Street Journal, and the in-state tuition at these colleges in the Integrated Post-secondary Education System database.

Results: We found a statistically significant but negligible correlation (Spearman rank correlation − 0.04, *p*-value < 0.0001) between the rank of a medical school and the total performance score of the hospitals that their graduates practiced in. We found a statistically significant and high correlation (Spearman rank correlation of − 0.903, *p*-value = 0.003) between the averaged rank of medical schools and average number of graduates produced by these schools associated with CMS hospitals. Similar results were obtained for the social mission score. In contrast, the correlation between the ranking of 4-year colleges and (a) their tuition was − 0.34 and (b) their outcomes was − 0.86 (p-value < 10^{-5}).

Conclusions: Our results suggest that US medical education is robust and produces satisfactory performance outcomes. Higher tuition is not correlated with higher ranks or better outcomes. Hence, the public needs to question what they are getting in return for higher tuition. We also suggest that it may be better to produce more graduates from existing medical schools than opening new schools.

Introduction and motivation

Given the high cost of healthcare in most countries, especially the USA, it is paramount to quantify and measure health outcomes as this leads to improved care delivery, cost reduction and efficiency [1]. This has led to large-scale data-driven approaches in health [2], with many government institutions worldwide embracing Open Data and transparency initiatives. In the US, the Center for Medicare and Medicaid Services (CMS) releases data continually about the physicians affiliated with CMS hospitals (https://data.medicare.gov/data/physician-compare) and the performance of CMS hospitals nationwide (https://data.medicare.gov/data/hospital-compare) [3]. Rao et al. review many of the benefits provided by this open data movement for healthcare [4–10]. For instance, the California Public Employees' Retirement System [11] reduced hip-replacement surgery costs for retirees by benchmarking these costs across hospitals.

One of the drivers of the high cost of healthcare in the US is the rapidly increasing cost of medical education. Hence, a significant amount of research has been devoted towards understanding the relation between cost, the types of medical schools and outcomes achieved by medical graduates [12–16].

Researchers have investigated different dimensions along which patient outcomes can be measured. Donaldson observes in [17][Foreword] that all interventions to treat patients are being measured on two major dimensions consisting of effectiveness and efficiency. The dimension of effectiveness has received the most attention, whereas the dimension of efficiency deserves more examination in the current climate of cost containment. Walsh [17][pg. 2] states that "Considering the cost of medical education, there is remarkably little known about its cost effectiveness. There is little known about how to calculate costs, about what constitutes costs or how to get maximal value for money. Up to now, there have been no books on this subject and precious few articles. Most of the articles that do exist are reviews that bemoan the lack of original research in this area. So, this is exciting territory."

Medical education in the US was reshaped significantly by the Flexner Report [18], which recommended that scientific inquiry and discovery should point the way to the future in medical education. Currently, there are many innovations being introduced into medical education, including web-based learning resources and simulations. New discoveries in the learning sciences have prompted questions about whether medical education needs to be changed [19]. Other important issues include: Can we produce competent physicians more efficiently and effectively? How can we reorganize medical education to produce physicians who are able to achieve better healthcare outcomes for the American people? These are valid questions, and significant research is required to inform policy makers appropriately. The issues of cost and value become mainstream only after several research efforts are published [14].

Against the backdrop of rising healthcarecosts in the US, it is important for the citizenry to question whether medical resources are addressing population needs across geographic regions and economic strata. Chen et al. [20] observe that the physician workforce in the US is struggling to address the adequacy of healthcare access in primary care and underserved areas. This creates a need to examine the outcomes of graduate medical education in order to better inform policy makers. For instance, it is important to determine whether medical graduates are serving the needs of the population as a whole, and if they are able to stay true to their core social mission of serving the sick and needy.

A related question about medical resources concerns the pipeline that produces medical professionals in the US. The AAMC has estimated that there will be a shortage of at least 100,000 doctors by 2030 [21]. On the other hand, Goodman and Fisher [22] challenge the popular observation that there is a shortage of physicians in the US. Important factors to consider include the distribution of physicians across regions that are underserved, and the variations in patient outcomes. Interestingly, having a larger supply of physicians does not imply improved patient outcomes. Furthermore, Medicare beneficiaries are just as satisfied with their care in high-supply regions as in low-supply regions. This raises the question of whether graduates of higher-ranked medical schools provide better patient outcomes than graduates of lower-ranked medical schools. This is one of the questions tackled in the current paper.

There are multiple challenges in defining and measuring outcomes in multiple fields, including education and healthcare. In the field of science education, it is difficult to define standardized measures of student performance [23]. Tracking student performance across multiple years is also a challenge. In the field of medical education, Chen et al. [20] state that it is difficult to measure outcomes as trainees traverse diverse paths while obtaining training at multiple institutions. Multiple approaches will be required for outcome measurements. In the current paper, we offer a big-data analytics perspective where multiple public datasets from the Center for Medicare and Medicaid Services (CMS) are joined with rankings data of medical schools.

A commonly used source to compare medical school rankings is the US News and World Report Rankings (https://www.usnews.com/best-graduate-schools/top-medical-schools). However, researchers have developed alternate rankings. Mullan et al. [16] state that medical schools have a social mission to care for the population. They developed a different ranking system by including measures for the number of underrepresented minorities in graduating medical classes, the percentage of medical graduates who practice primary care, and the number who work in areas with health professional shortages. This resulted in a composite measure, the social mission score, and was used to rank medical schools.

The goal of the current paper is to seek solutions to the following questions: 1) What is the relationship between the rank of medical schools and the outcomes achieved by medical graduates? (2) What is the relationship between the social mission rank of medical schools and the outcomes achieved by medical graduates? (3) What are the relationships between rank, social mission rank and the costs of attending medical schools? We use a Big-data approach that offers an unprecedented look at measuring the performance of professionals in medical institutions nationwide. We derived our data from public sources, including the Medicare Dataset [3, 4]. We applied correlation and linear regression analysis in order to examine the three questions stated above.

The work in our paper contributes to our understanding of the relationship between cost and value using Big Data analytics. Our research addresses a controversy in the medical field about the current number of medical graduates being produced and whether this needs to be increased [24]. Patients and the interested public need to understand how government healthcare expenditure impacts public health and can play an important role by being vigilant about the options available to them. An increasing number of researchers are applying machine learning and advanced analytic techniques to analyze and interpret healthcare data [4, 10, 25, 26]. The free dissemination and availability of data analytics platforms such as the one we are building [8] will facilitate the exploration and interpretation of such healthcare datasets by patient advocacy groups and concerned citizens at large [5].

Related work

The medical education field aims to align education with outcomes [27]. Outcomes measurement becomes challenging once students begin medical practice. As Prystowsky and Bordage [13] observe, "Often, data are impossible to obtain because they are either confidential or simply not recorded, or because the practice location is unknown. There are also many confounding variables in measuring patient outcomes." The release of large amounts of data related to physicians and hospital performance scores [3, 4] based on patient outcomes provides an interesting opportunity to address these issues.

The cost of medical education is also a large concern. The article by Prystowsky and Bordage [13] written in 2001 noted that the zeitgeist at that time was cost containment, and that substantial variability existed in student tuition amongst US medical schools. This raised fundamental questions about factors driving the cost of medical education and whether outcomes could justify the cost. This would lead to better-informed policy decisions, geared towards maximizing efficiency and towards using the right priorities. Interestingly, the situation seems to have remained the same, as we appear to be no closer to cost containment or maximizing efficiency. However, our data collection, dissemination and analytics capabilities have vastly improved over the past 15 years, and this demands a fresh examination of these issues from a data-driven perspective.

Thakore [12] notes that "There is an imperative to make postgraduate medical education cost-effective. However, this can only be achieved if we know what we are producing and how much it currently costs to produce it." This is a challenge that persists today across multiple nations. There are two important aspects to consider. The first concerns the definition of the appropriate variables to measure and collection of the necessary data. The second concerns the methodology that is used to perform the analytics and whether it is easily repeatable and verifiable by multiple researchers. This is because new data will be created each year, and a self-sustaining mechanism is required, which can refresh the results periodically. Evidence that contributes to an understanding of cost-effectiveness can be gathered from many sources. We provide an open-data approach to shed light on this question, and illuminate the current debate about the value provided by medical education.

Medical education is expensive across the world. The cost of medical education needs to be examined from both a student's viewpoint and a societal viewpoint. Governments worldwide are becoming very sensitive to the cost borne by taxpayers. As Walsh [28] observes, "The public will only tolerate funds being spent on medical education when they know that such funding is delivering the maximum possible returns."

The data surrounding the relationship between procedure costs and outcomes is intriguing. A recent study by Tsugawa et al. [29] based on over 20,000 physicians found that higher physician spending is not associated with improved patient outcomes.

Raghupathi and Raghupathi [30] show that many applications in healthcare meet the four accepted criteria to be worthy of being termed "big-data", which are volume, velocity, variety and veracity. They specifically mention the use of outcome data, including patient outcomes. Our current paper is primarily concerned with the aspects of volume, variety and veracity. We present a framework that can analyze large public healthcare datasets released by CMS [3, 4]. Precise calculations which support the characteristic of high "volume" in the big-data definition as applied to public healthcare data can be found in Rao and Clarke [7]. We use data from 895,431 unique healthcare practitioners in the US, which represents nearly 75% of the practicing workforce in many specialties. This is a remarkably high coverage for such a study (workforce assessments done with even 3% of the workforce are typically considered meaningful [31]). The characteristic of "variety" is also applicable to our work, as data from multiple sources, including federal agencies and private sector websites have to be integrated to answer specific research questions. The characteristic of "veracity" is important in our current paper, as missing and/or incorrect data may be present in these sources. Hence, we used different techniques including outlier detection to identify problems in the public healthcare datasets. For instance, the graduation years of a few providers in the CMS [3, 4] data were well beyond the life expectancy of current providers. These had to be explicitly filtered out prior to our analysis. As pointed out by Raghupathi and Raghupathi [30], traditional data management techniques assume the data is clean. However, public healthcare data does not meet this assumption, and we had to invest significant effort in cleaning the data before utilizing it. Researchers have estimated that data cleaning accounts for about 30–80% of the time and budget in commercial big data projects [32]. The quality of velocity [30] does not apply to the data in our paper as we are not considering streaming data sources.

Obtaining performance information in the medical field is challenging, as most public websites are not reliable. For instance, Rosenkratz [33] studied the availability and accuracy of price and performance information of radiology practices on public websites, and determined that performance information usually presented is not of adequate clinical quality. Hence, we used data from a federal source, CMS, where more rigorous techniques are used for ensuring data quality.

Methods

Our original data analysis framework [4], shown in Appendix: Fig. 5, consisted of the following steps: data cleansing/ETL, data joining, feature engineering, clustering classification and prediction, visualization of results, interpretation and reporting.

We used public data for our analysis, consisting of data from CMS, medical college ranking data from two sources, and the cost of medical colleges from the AAMC.

Data from Medicare

We joined Medicare-provided data from CMS [3, 4] residing in the following files.

1. A file containing the hospital id and physician information: https://data.medicare.gov/Physician-Compare/National-Downloadable-File/s63f-csi6, henceforth referred to as "National-Downloadable-Physician-Compare". Sample data are shown in Appendix: Fig. 6.
2. A file containing the hospital id and hospital performance metrics provided by the CMS addressing processes, outcomes and cost. A total performance score in the range 0–100 is provided by CMS, which was used in our analysis. Further details about these metrics can be found in http://www.medicare.gov/hospitalcompare/data/total-performance-scores.html. Sample data are shown in Appendix: Fig. 7.

The CMS office uses a standardized procedure [3, 4] to evaluate hospitals across the US, based on the generated outcomes for Medicare/Medicaid patients. Four domains are combined to produce the final "Total Performance Score" and consist of the following: (1) Clinical Care domain comprised of process and outcomes subdomains, (2) Patient-and Caregiver Centered Experience of Care/Care Coordination domain, (3) Safety Domain, and (4) Efficiency and Cost Reduction domain. The Clinical Care domain produces clinical process measures and measured mortality. The Patient-and Caregiver Centered Experience of Care/Care Coordination domain addresses patient surveys. The Safety domain covers patient safety measures, including measures of infections. The Efficiency and Cost Reduction domain utilizes a measure of the Medicare spending per beneficiary.

The CMS office computes a weighted average of these measures from the four domains. Though these measures are authoritative, as they are released by the Federal Government, they are constantly improved upon. For instance, a current shortcoming is that the information derived from patient surveys could be potentially biased. It is likely that patients with the best or worst experiences may be more likely to complete these surveys. Furthermore, some of the survey questions are prefixed with "Always", which may make it hard for patients to choose an appropriate response. Hence, the validity of these performance measures continues to be actively researched and debated [34]. This analysis falls outside the scope of the current paper.

Press [35] showed that several factors need to be taken into account in defining performance measures, including whether a measure occurs prior to or during the care, and the application of appropriate risk adjustments. Kernisan [36] determined that there was no association between a hospital's self-reported safe practices survey score and risk-adjusted patient mortality. Leonardi [37] compared different websites containing hospital performance data, and found that the CMS Hospital Compare website was the most transparent in terms of explaining data sources and statistical methods that allow their exact results to be duplicated.

Hence, we choose to use "as-is" the Federally approved measures in the CMS database. Data from 895,431 unique practitioners was joined with data from 3089 unique hospitals. This CMS data has a remarkably high coverage of the total number of medical practitioners in USA as determined by the AAMC, and exceeds 75% for several medical specialties.

Medical school rankings and costs

The CMS data contains the field "Medical school name." We used two sources of ranking information about these medical schools. We first obtained a ranking of medical schools from http://medical-schools.startclass.com/. (Note that this website is unavailable. However, as explained later, we have made this data available, and also compared it with rankings that are currently available, such as https://www.usnews.com/best-graduate-schools/top-medical-school). This ranking is based on each school's statistics, such as mean GPA, average MCAT score, acceptance rate, faculty-student ratio, financial aid and endowment per student. A sample of the rankings is provided in Appendix: Fig. 8. We used this source as the ranks were easily downloadable as an Excel file. An alternate source of ranking is provided by US News and World Report at https://www.usnews.com/best-graduate-schools/top-medical-schools. The rankings produced by these two sources are highly correlated, with a correlation value of 0.85 ($p < 0.001$, indicating that the result is statistically significant). A scatterplot of these two ranking systems is shown in Appendix: Fig. 9. (We note that the site http://medical-schools.startclass.com has been withdrawn since this paper was prepared. The original data used in our analysis will be made available at www.github.com/fdudatamining so others can replicate our results. Furthermore, the statistically significant and high correlation between the two ranking systems should provide similar inferences about the datasets we analyzed). The second source of ranking information we used was based on the Social Mission Score, developed by Mullan et al. [16], which includes factors such as the number of graduates practicing in underserved areas.

After joining these data sources, we can determine the medical school that a practitioner graduated from, two types of estimated medical school ranks, the hospitals associated with the practitioner, and the performance score received by that hospital from CMS. Our subsequent analysis was based on a collection of such entries over all the data provided by the CMS. We explored whether the composition of the practitioners in a hospital based on the caliber of the institutions they graduated from was related to a metric of hospital performance.

Finally, we obtained medical school costs from https://www.aamc.org/data/tuitionandstudentfees/ [38].

Results

The CMS data represents 407 unique institutions from which 895,431 practitioners graduated. We obtained 602,770 entries of the form shown in Appendix: Fig. 9, consisting of practitioners associated with ranked medical schools. Note that the entries that were dropped either contained medical schools denoted by "OTHER" or medical schools that were not in the list of ranked medical schools. A reason for the occurrence of "OTHER" is that the health practitioner may have obtained a degree from a foreign medical institution. This constitutes a limitation of the data, and also illustrates the type of processing required to maintain "veracity", one of the four Vs of Big Data. This is a point raised by Raghupati and Raguhupati [30] where we go beyond traditional data management techniques which assume the data is clean.

Distribution of practitioners from medical schools with known rank

We computed the distribution of practitioners of medical schools with a given rank across the CMS database as shown in Fig. 1a. The Spearman Rank Correlation

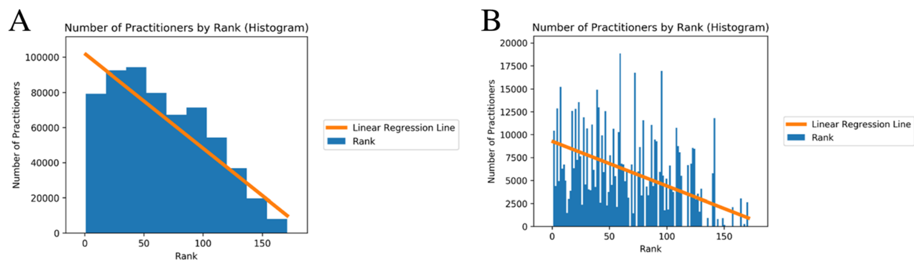


Fig. 1 a This figure is a histogram of the number of practitioners in CMS hospitals according to the rank of the medical schools they graduated from. The rank of a medical school is shown on the x axis, whereas the y-axis shows the number of graduates from that medical school participating in hospitals in the CMS database. Ranks were binned in bins of size 10. The fit line using linear regression is expressed as $N = -538R + 102{,}024$ where N is the number of practitioners and R is the binned rank of a medical school. The goodness of fit metric, r-squared, is 0.86. **b** This figure shows a histogram of the number of practitioners in CMS hospitals according to the rank of the medical schools they graduated from. No binning of ranks was performed. The fit line using linear regression is expressed as $N = -49R + 9273$ where N is the number of practitioners and R is the rank of a medical school (r-squared = 0.27)

coefficient between the binned rank of a medical school and the number of practitioners shown in Fig. 1 was − 0.903 (p-value = 0.003). The Spearman Rank Correlation coefficient between the rank of a medical school and the number of practitioners shown in Fig. 1b was − 0.568 (p-value < 0.0001).

Relationship between the rank of a medical school and the performance scores of hospitals

A heatmap was used to explore the relationship between the rank of a given medical school and the performance scores of hospitals that graduates from this medical school practice in. The heatmap in Fig. 2a provides a nuanced view of the variation between these two dimensions. Let us denote the rank dimension by "r" and the performance score dimension by "s." Each pixel or location in the heatmap, say H1(r, s) is addressed

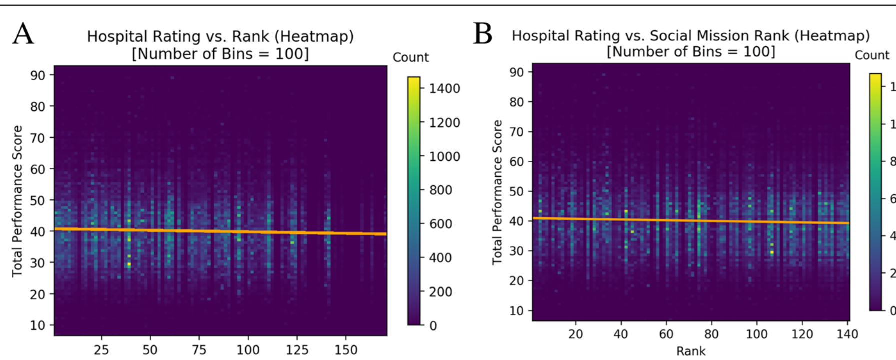


Fig. 2 a This figure examines the relationship between the rank of medical school and the performance score associated with hospitals their graduates practice in. The data is shown in the form of a heatmap. The orange line represents the linear fit regression line, which has the form $S = -0.0984R + 40.76$ where S is the total performance score, and R is the rank of a medical school (r-squared = 0.001). **b** This figure examines the relationship between the social mission rank of medical school and the performance score associated with hospitals their graduates practice in. The data is shown in the form of a heatmap. The orange line represents the linear fit regression line, which has the form $S = -0.0123R + 40.95$, where S is the total performance score, and R is the social mission rank of a medical school (r-squared = 0.002) by two coordinates: a rank “r” and a performance score “s.” Consider a rank say “r0” which represents a medical school, and a performance score say “s0.” We compute the total number of entries in our database that have rank “r0” and performance score “s0”. This number is color-coded and forms the color of the pixel at (r0, s0) in the heatmap. This way, we can observe the distribution of performance scores of hospitals that graduates from that school belong to.

The Spearman Rank correlation coefficient between the rank of a medical school and total performance score across the hospitals that its graduates practice in is – 0.04 ($p <$ 0.0001). Figure 2b shows the heatmap of the social mission rank versus total performance score. The Spearman Rank correlation coefficient between the social mission rank of a medical school and total performance score across the hospitals that its graduates practice in is – 0.044 ($p < 0.0001$).

Distribution of practitioners from medical schools across CMS hospitals

We explore the relationships between graduates of medical schools and the CMS hospitals they practice in.

Exploring the relationship between rank of a medical school and cost of attendance

We downloaded data describing the cost of attending medical schools from https://www.aamc.org/data/tuitionandstudentfees/ [38]. We joined this data with the medical school rankings obtained from http://medical-schools.startclass.com/. We used this joined data to explore the relationship between the rank of a medical school and the cost of attending that school. The data is presented in the form of a scatter plot in Fig. 4a. The Spearman Rank correlation coefficient between the rank of a school and the cost of attendance is – 0.169, and the p-value is 0.21, which is greater than the typically used significance threshold of 0.05. Hence, there is no statistically significant relationship between these two variables.

However, Fig. 4b shows that the social mission rank of a medical school has a statistically significant correlation with the cost of attending medical school. The Spearman Rank correlation coefficient is 0.21, p-value = 0.03.

Figure 4c and d enumerate medical schools with the lowest and highest costs of attendance

Discussion

It is important for the public to make informed decisions both at the level of personal spending and at the level of societal spending. We adopted a Big Data approach by joining multiple large public datasets. Our framework and methods close the gap between the availability of public healthcare data and our ability to extract meaning and value from this data. We have made our tools and techniques open-source [39], which should facilitate further analysis by the research community.

A concern about the future of the medical work force in the US is a projected dearth of medical graduates in different specialties [40], creating a potential crisis [41]. However, this is controversial, as some researchers do not see a shortfall [24] and suggest alternatives to increasing the supply of medical graduates in the US [42]. Hence, it is important to understand the factors governing the supply of medical graduates, including the specific institutions that produce them, the ranking of these institutions and relationships between these factors.

Figure 1 examines the relationship between the number of practitioners in CMS hospitals from specific medical schools and the ranks of those schools. There is a statistically significant and moderately high inverse correlation between these two variables. The fit of the regression line indicates that lower ranked schools (that lie towards the right on the x-axis) produce fewer graduates that practice in CMS hospitals. From a policy point of view, it is important to consider the overall impact that medical graduates have, including their social mission [16] to serve public health needs. Hence, it may be advantageous to increase the number of graduates from existing well-ranked medical schools.

Clarke [43] observes that it is difficult to examine the effect of an institute's ranking on the outcomes achieved by its graduates. The small amount of existing research focuses on employment and earnings outcomes. In the area of business schools, the higher the rank, the higher the starting salary of their graduates. This is partly due to the fact that business schools have no licensing requirements that their graduates need to obtain. In contrast, medical school graduates need to be licensed.

Given the difficulty other researchers have faced in establishing relationships between the ranking of an institute and outcome, the research presented in the current paper offers an alternative approach where an outcome related to the quality of care provided is utilized. This is a novel method utilizing publicly available data to explore the relationship between the rank of a medical college and the total hospital performance score achieved by its graduates. This outcome measure is indirect, as it does not directly measure the performance of an individual medical graduate, but measures the net effect of multiple medical graduates and hospital administration.

An inherent limitation in the data we use is that we are not able to consider the performance of physicians in private practice or non-CMS hospitals. This is inherited from the type of data that the US federal government wishes to make transparent, which currently applies only to some aspects of the functioning of CMS hospitals.

The data in Fig. 2a indicates that the correlation between medical school rank and the performance score of hospitals their graduates practice in is statistically significant but low. A similar result is obtained in Fig. 2b for the social mission score. A possible explanation is that the standardization of medical education [44] and the medical licensing examination sets a high bar for medical students. Passing this examination guarantees that a graduate will produce satisfactory patient outcomes. This is reassuring to the public, suggesting that the medical education provided in the US is robust, and that the graduates are well poised to be successful. Our finding is consistent with the observations of Cooke et al. [19]. Unlike Flexner, Cooke et al. [19] did not find great disparities in the quality of education among the medical schools they visited. Two important contributors were accrediting and licensing systems.

An important underlying issue concerns the derivation of a single or a few quality metrics that characterize an institution such as a hospital or a medical college. Greco et al. [45] and Lascano et al. [46] discuss several important factors in creating composite quality measures such as the complexity of the problem and potentially confounding variables. For instance, there are few studies that examine statistical relationships between patient and hospital characteristics and outcomes. Fonarow et al. [47] developed hospital mortality models for acute ischemic stroke patients. The hospital characteristics were measured by variables such as the number of beds, the regional location of the hospital and whether the hospital type was teaching or non-teaching. However, no metric related to the actual care providers, such as seniority or experience was captured. At a higher organizational level, factors such as management structure and motivation of the employees [48] could also play a role in outcomes, though this will be harder to measure.

In a broader context, studies have shown that many top employers hire very selectively [49]. Interestingly, such analyses are being enabled with the current data revolution, where detailed personal information is available. For instance, an analysis of LinkedIn data showed that Facebook and Google hire more than 80% of their employees from the top 200 schools in the US [49]. Hence, one can argue that graduates of these highly ranked institutions provide high performance (or value) to the companies that hire them, and this can be measured by outcomes such as the growth rate or market valuation of the company. However, such a case cannot be made for the hospitals based on the currently defined outcomes scores [3]. It may indicate either that there is no such easily determinable relationship, or that the outcomes scores are imperfect. Several researchers have already suggested that better metrics are needed to compare hospitals [45, 46, 50]. Given that the outcomes score is currently fixed, it is likely that the ranking of the medical school that the physician graduates from is not affecting the currently used outcome score of the hospital.

Recent research by Tsugawa et al. [51] shows that there is little to no relationship between the ranking of a medical school that a physician graduates from and the 30-day mortality or readmission rates of the patients treated by this physician. Our results are consistent with the results reported by Tsugawa et al. [51], which used more detailed data provided by the source doximity.com. However, this data source is available only to clinically licensed healthcare professionals, and some parts of the data may require fees. In contrast, we used data sources that are both free and open to the public, which enables easy and independent verification. Furthermore, an advantage of our approach is that our methodology can be repeatedly applied on new data as they are periodically released by agencies such as CMS on a quarterly or annual basis. We have also made the software environment freely available on github [39], which enables transparency and easy replication of our results. Furthermore, our current paper also discusses the relationship between the cost and ranking of medical schools, which is not present in other papers.

Our results are also consistent with the work of Reid et al. [52] who observed no statistically significant associations between physician performance and physician characteristics such as allopathic vs. osteopathic degree, medical school rankings, or years of experience. Reid et al. [52] analyzed data for about 10,000 Massachusetts physicians and found that board certification was associated with high performance scores.

A study by Hartz et al. [53] showed that outcomes for coronary bypass surgery carried out by a sample of 275 surgeons were not associated with the prestige of the medical schools that graduated from. They noted that the prestige of an institution affects its ability to attract students, and that a patient's assessment of the quality of a physician may be influenced by where the physician trained. Nevertheless, these factors did not appear to affect clinical outcomes.

An example of the rank of a medical school affecting medical practice is provided by Schnell and Curie [54], who found that physicians who graduated from higher ranked medical schools wrote significantly fewer opioid prescriptions than physicians from lower ranked medical schools.

Our analysis of the relationship between medical college rank and the CMS hospital score could spur further research about defining appropriate quality metrics for medical care and outcomes.

We performed a related analysis [55] of the relationship between the seniority of providers from the CMS database and the performance of the hospitals they practiced in. We determined a statistically significant but low correlation between seniority and hospital performance score, which suggests that the medical training obtained by the providers positions them for long careers in healthcare. In this sense, the finding in Rao [55] is consistent with the finding of the current paper in that the standardization of medical education has worked well in the service of society.

van der Leeuw [56] performed a comprehensive review of existing studies to determine the effect of residency training on patient outcomes, and found that patient care delivered by residents was safe and of equal quality. There is a tradeoff between the number of medical practitioners utilized in these studies and the detail at which outcomes are measured. The number of medical practitioners in studies cited by van der Leeuw [56] range from about a hundred [57] to about four thousand [58]. In contrast, the current paper utilized around 600,000 medical practitioners at a coarse level of outcome measurement. Our results are consistent with the findings of van der Leeuw [56], and may be viewed as a limit case when the sample size becomes very large. This is a novel result in the field of healthcare informatics.

A limitation of our result is that it is obtained at a coarse level, where an aggregate performance measure, the CMS hospital score is correlated against the medical college ranks of physicians at these hospitals. This is a consequence the granularity of the open data that we used.

Figure 3 highlights three medical schools that are in the top 20 ranked schools and also produce the top 20 numbers of graduates practicing in CMS hospitals. This indicates that being highly ranked does not exclude a college from producing a large number of graduates who serve in CMS hospitals. From a policy standpoint, it may be interesting to examine the characteristics of the following three medical schools: the University of Washington Medical School, the University of Michigan Medical School and the University of Minnesota Medical School. There could be shared characteristics that other medical schools may want to emulate. Furthermore, from a national medical budget appropriation standpoint, it may make sense to allocate additional funds to highly ranked institutions that also supply a sufficient number of graduates who work in CMS hospitals. The technique provided in our paper suggests a method to reward highly ranked medical schools that achieve a social mission.

The data in Fig. 4a shows that there is no statistically significant relationship between the cost of attending a medical school and its rank. Furthermore, we observe from Fig. 2 that the correlation between medical school rank and the performance score of hospitals their graduates practice in is weak. These two results suggest that if a prospective medical school applicant is interested primarily in medical practice at CMS hospitals, A

Count	School	Rank
7265	INDIANA UNIVERSITY SCHOOL OF MEDICINE	39
6806	WAYNE STATE UNIVERSITY SCHOOL OF MEDICINE	96
6535	UNIVERSITY OF MINNESOTA MEDICAL SCHOOL	20
5919	OHIO STATE UNIVERSITY COLLEGE OF MEDICINE	35
5763	TEMPLE UNIVERSITY SCHOOL OF MEDICINE	72
5727	UNIVERSITY OF ILLINOIS AT CHICAGO HEALTH SCIENCE CENTER	59
5488	PHILADELPHIA COLLEGE OF OSTEOPATHIC MEDICINE	141
5417	UNIVERSITY OF MICHIGAN MEDICAL SCHOOL	7
5409	JEFFERSON MEDICAL COLLEGE OF THOMAS JEFFERSON UNIVERSITY	58
5195	UNIVERSITY OF TENNESSEE COLLEGE OF MEDICINE	91
5169	NEW YORK MEDICAL COLLEGE	124
4919	UNIVERSITY OF KANSAS SCHOOL OF MEDICINE	46
4917	UNIVERSITY OF ALABAMA SCHOOL OF MEDICINE	40
4888	GEORGETOWN UNIVERSITY OF MEDICINE	54
4716	MEDICAL COLLEGE OF GEORGIA	110
4699	LOUISIANA STATE UNIVERSITY SCHOOL OF MEDICINE IN NEW ORLEANS	123
4607	UNIVERSITY OF TEXAS MEDICAL BRANCH AT GALVESTON	111
4542	UNIVERSITY OF TEXAS SOUTHWESTERN MEDICAL SCHOOL AT DALLAS	23
4510	UNIVERSITY OF IOWA COLLEGE OF MEDICINE	25
4379	UNIVERSITY OF WASHINGTON SCHOOL OF MEDICINE	5

B

Rank	School	Count
1	HARVARD MEDICAL SCHOOL	4083
2	UNIVERSITY OF CALIFORNIA, SAN FRANCISCO SCHOOL OF MEDICINE	3118
3	JOHNS HOPKINS UNIVERSITY SCHOOL OF MEDICINE	3023
4	UNIVERSITY OF PENNSYLVANIA SCHOOL OF MEDICINE	4083
5	UNIVERSITY OF WASHINGTON SCHOOL OF MEDICINE	4379
6	UNIVERSITY OF CALIFORNIA, UCLA SCHOOL OF MEDICINE	3576
7	UNIVERSITY OF MICHIGAN MEDICAL SCHOOL	5417
8	UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL SCHOOL OF MEDICINE	3720
9	UNIVERSITY OF PITTSBURGH SCHOOL OF MEDICINE	3675
10	STANFORD UNIVERSITY SCHOOL OF MEDICINE	1771
11	UNIVERSITY OF CHICAGO, PRITZKER SCHOOL OF MEDICINE	2491
12	WASHINGTON UNIVERSITY SCHOOL OF MEDICINE	3071
13	MAYO MEDICAL SCHOOL	1072
15	UNIVERSITY OF CALIFORNIA, SAN DIEGO SCHOOL OF MEDICINE	2160
16	CORNELL UNIVERSITY MEDICAL COLLEGE	2400
17	VANDERBILT UNIVERSITY SCHOOL OF MEDICINE	3227
18	BAYLOR COLLEGE OF MEDICINE	4263
19	UNIVERSITY OF WISCONSIN MEDICAL SCHOOL	4084
20	UNIVERSITY OF MINNESOTA MEDICAL SCHOOL	6535

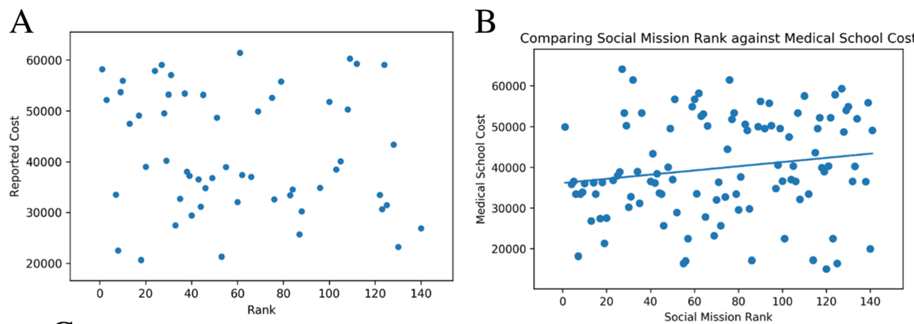
Fig. 3 a This is a sorted list containing the top 20 medical schools that have the most graduates practicing in any hospital in the CMS database. The "Count" column indicates the number of such graduates. The entries are sorted in decreasing order of "Count." The highlighted entries are schools that are ranked in the top 20 medical schools. **b** This is a sorted list containing the top 20 medical schools by rank. The "Count" column indicates the number of graduates practicing in any hospital in the CMS database. The same highlighted medical schools in Fig. 3a are highlighted here

the specific school he or she attends may not matter. Graduates from both higher-ranked and lower-ranked schools can achieve similar outcomes when they practice at hospitals in the CMS database.

Figure 4 on the other hand shows that there is a statistically significant correlation between the social mission rank of a medical school and the cost of attendance of that school. The correlation has a low positive value of 0.21, which indicates that as the numerical social mission rank increases (i.e. the social mission of the school decreases), the cost increases

Figure 4c and d compare the costs at the lowest ten and top ten schools sorted by cost of attendance, along with the social mission rank and traditional rank. These tables show that it is possible for schools to be well ranked in social mission measures and traditional measures and still have a low cost of attendance. Furthermore, we note that several medical schools in the state of Texas have the lowest cost of attendance. Determining the shared characteristics of these schools should provide guidance to policy makers on factors governing cost-effective medical education

We note that private and public medical colleges vary greatly in their costs. Figure 4c show that there are several private colleges that cost more than $55,000 per year, whereas Fig. 4d shows several public colleges, notably in Texas that cost less than $18,000 per year. This is likely because tuition at public colleges is subsidized by state funding. A recent article [59] examines some of the factors surrounding the low cost of attendance of Texas medical schools. Policymakers were aware of the rapid growth of the state's population, which created significant physician shortages. So the state invested in creating new medical schools and also capped the tuition at these schools. The majority of medical graduates from these schools stay in Texas. Our results in Fig. 4a show that the quality of the schools are not compromised, as many of them have respectable ranks.



C

School	Cost	Social Mission Rank	Rank
UNIVERSITY OF TEXAS MEDICAL SCHOOL AT HOUSTON	15096	120	73
TEXAS A & M UNIVERSITY COLLEGE OF MEDICINE	16432	55	101
UNIVERSITY OF TEXAS MEDICAL BRANCH AT GALVESTON	17051	56	111
UNIVERSITY OF TEXAS MEDICAL SCHOOL AT SAN ANTONIO	17133	86	70
TEXAS TECH UNIVERSITY HEALTH SCIENCE CENTER SCHOOL OF MEDICINE	17189	114	104
EAST CAROLINA UNIVERSITY SCHOOL OF MEDICINE	18159	7	56
UNIVERSITY OF TEXAS SOUTHWESTERN MEDICAL SCHOOL AT DALLAS	19923	140	23
UNIVERSITY OF NEW MEXICO SCHOOL OF MEDICINE	21303	19	53
STANFORD UNIVERSITY SCHOOL OF MEDICINE	22459	123	10
UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL SCHOOL OF MEDICINE	22459	57	8

D

School	Cost	Social Mission Rank	Rank
MEDICAL UNIVERSITY OF SOUTH CAROLINA COLLEGE OF MEDICINE	61436	32	62
TUFTS UNIVERSITY SCHOOL OF MEDICINE	61436	76	61
ALBANY MEDICAL COLLEGE OF UNION UNIVERSITY	59271	127	112
HARVARD MEDICAL SCHOOL	58151	62	1
DUKE UNIVERSITY SCHOOL OF MEDICINE	57870	124	24
GEORGETOWN UNIVERSITY OF MEDICINE	57516	110	54
GEORGE WASHINGTON UNIVERSITY SCHOOL OF MEDICINE	56733	60	77
YALE UNIVERSITY SCHOOL OF MEDICINE	56725	51	32
WASHINGTON UNIVERSITY SCHOOL OF MEDICINE	56212	90	12
NORTHWESTERN UNIVERSITY MEDICAL SCHOOL	55885	139	22

Fig. 4 **a** This figure shows a scatter plot of the rank of a medical school on the x-axis versus the cost of attending that school on the y-axis. The cost reported consists of the in-state tuition, fees and insurance per student. **b** This figure shows a scatter plot of the social mission rank of a medical school on the x-axis versus the cost of attending that school on the y-axis. The cost is reported consists of the in-state tuition, fees and insurance per student. The linear fit regression line has the form $C = 51.6\ S + 36{,}130$ where S is the social mission rank of a medical school and C is the cost of attendance. (R-squared = 0.029) **c** This figure shows the ten medical schools with the lowest cost of attendance (for in-state students). Their social mission rank and traditional rank are also included. **d** This figure shows the ten medical schools with the highest cost of attendance (for in-state students). Their social mission rank and traditional rank are also included.

Several research studies have shown a preference amongst physicians to locate in the same geographic area as their residency [20]. Chen at al. [20] measured the impact of residency programs on regional physician workforces. Their analysis addressed some of the traditional difficulties in tracking the variable career paths of the trainees and the arrangements between training institutions. It follows that if it is desirable from a social mission viewpoint [16] to have more physicians practice in rural areas, then the graduate medical education (GME) program in the US should encourage exposure of residents to rural and underserved areas. Accordingly, there has been an examination of the accountability of GME starting as early as 1965 [60] and continuing through the current decade [61]. Greater transparency is a particular concern among the public [62]. Indeed, transparency is a central theme of our paper, and we focus on the analytics in order to derive insights from data released through transparency efforts.

An emerging theme advocated by Shannon [63] is that more attention needs to be paid to osteopathic medical schools, as 60% of their graduates practice primary care, and many are located in rural areas. The growing cost of medical education is turning many entrants away from aspiring to be primary care physicians. This raises challenges for students, the medical institutions and the entire health system [63]. Indeed, the cost of medical education is an important variable in the analysis of the current paper. However, translating these observations into policy decisions remains challenging, and subject to contentious debates, as the recent Institute of Medicine report on GME illustrates [64].

In our analysis, we have focused on the cost of medical school and not elaborated on the role that GME plays in the training of physicians. The cost of GME is subsidized by support from Medicare and Medicaid and a review of its history can be found in [65]. Though the public is aware of the value of this subsidy [66], there is debate about its maintenance and continued expansion [64].

We contrast the results we have obtained for medical schools with similar calculations we carried out for colleges offering 4-year baccalaureate degrees in the US [67]. We obtained rankings of colleges from the Wall Street Journal (https://www.wsj.com/graphics/college-rankings-2018-tool/). We obtained the in-state tuition to attend these colleges from IPEDS (Integrated Postsecondary Education Data System, https://nces.ed.gov/ipeds). The correlation between the rankings of the top 500 colleges and their in-state tuition is − 0.34 (p-value $< 10^{-5}$). This is a moderate and statistically significant correlation. The negative sign indicates that the higher the ranking, the more it costs to attend the institution, as the top-500 list contains about 380 private colleges and 120 public colleges. The Wall Street Journal rankings also includes a measure for the outcomes of each college, and is calculated based on graduation rates, the value added to graduate salary, loan defaults and academic reputation. The correlation between the outcomes score and rank for the colleges as reported by the Wall Street Journal was − 0.86 (p-value $< 10^{-5}$). This is a high value, and indicates that better ranked colleges produce better outcomes. A detailed analysis of the methodology behind the Wall Street Journal rankings is outside the scope of this current article. An excerpt of our analysis is presented in the Appendix, Fig. 11.

This finding is interesting, as there is no such relationship for medical colleges, where higher costs are not correlated with either better ranks or better outcomes.

With the rising costs of college on the minds of a good fraction of our youth, studies are pointing to the diminishing returns that college degrees are conferring on students [68]. It is important for the public to understand what they receive in return for paying for college. Paradoxically, for an investment of this magnitude, it is especially hard to evaluate the quality of education provided. In a recent news article [69] highlighting this issue, the Director of the Georgetown University Center of Education observed “when it comes to how students select a college, we are clueless about quality. The proxy we use is reputation.” Hence, rankings of colleges are popular as they serve to measure reputation. The research presented in the current paper shows that with some effort, it is possible to delve deeper, and investigate important relationships between cost, reputation and outcome. This will help the public make better decisions, in terms of both choosing where and how to spend dollars as individual student consumers, and choosing how to spend dollars as a nation for medical education.

A limitation of this study is that it utilizes only open health data. Furthermore, the total performance score of a hospital is representative of the average performance of all the hospital employees, including healthcare professionals and hospital administration. This measure does not capture the performance of an individual practitioner.

As many governments continue to release data about the workings of the healthcare system, we can expect the type of analysis we presented to become more popular. For instance, New York State, under the Statewide Planning and Cooperative Research System (SPARCS), has released data about specific outcomes achieved by cardiac surgeons [70]. Thus, we expect to see an improvement in the ability of the public to perform due diligence, verify the outcomes of government expenditures, and examine the routes for effective utilization of societal resources including capital and the workforce. This is not possible without access to the data as well as computational tools and algorithms to process the data. By making our tools and techniques open-source [39], we expect the barriers to perform this type of analysis to be lowered significantly.

Conclusion

Our paper highlights the use of Big Data analytics based on open healthcare data to explore relationships related to the cost of medical education, reputation of medical schools measured by rankings and outcomes. We found a statistically significant but negligible correlation between the rank of a medical school and the total performance score of the hospitals that their graduates practiced in. For the social mission rank, we obtained a similar result. These results suggest that US medical education is robust in terms of producing satisfactory performance outcomes of medical graduates. Higher tuition is not correlated with higher ranks or better outcomes. No statistically significant correlation was found between the rank of a medical school and the cost of attendance. There is a statistically significant but weak correlation between the social mission rank of a medical school and the cost of attendance. Hence, the public needs to question what they are getting in return for higher tuition.,

We found a statistically significant and high correlation between the averaged rank of medical schools and average number of graduates produced by these schools that are associated with CMS hospitals. This suggests that it may be better to add capacity to higher ranked medical schools that place graduates in CMS hospitals than open newer schools that may have a lower ranking. Several medical schools we have identified have lower cost, and produce acceptable outcomes. Further investigation should focus on common characteristics of these schools that can be replicated to improve the cost effectiveness of medical education in the US.

A unique component of our research is that we have released our analysis code to the public via an open source repository (www.github.com/fdudatamining). This will

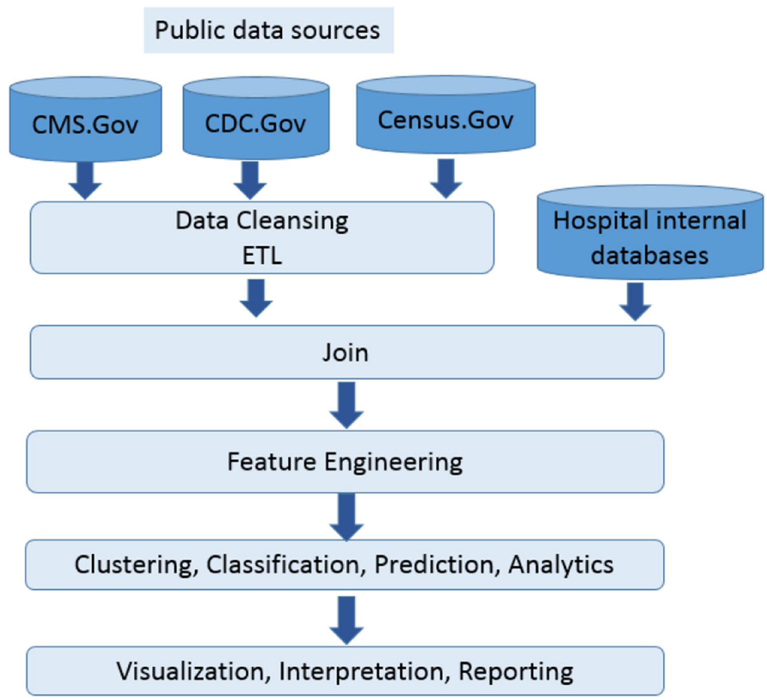


Fig. 5 Data Analysis Framework

NPI	1245439843	1932137122
PAC ID	7719077189	4587839238
Professional Enrollment ID	I20071221000416	I20111208000600
Last Name	WALFISH	PETERS
First Name	MENACHEM	NANCY
Middle Name		J
Suffix		
Gender	M	F
Credential		
Medical school name	MOUNT SINAI SCHOOL OF MEDICINE OF CITY UNIVERSITY OF NEW YORK	OTHER
Graduation year	2003	1982
Primary specialty	ANESTHESIOLOGY	INTERNAL MEDICINE
Secondary specialty 1		
Secondary specialty 2		
Secondary specialty 3		
Secondary specialty 4		
All secondary specialties		
Organization legal name	SILVER MEDICAL PC	ASSOCIATED PHYSICIANS OF WESTERN NEW YORK P.C.
Organization DBA name		
Group Practice PAC ID	6709075070	1052394301
Number of Group Practice members	6	5
Line 1 Street Address	1630 E 14TH ST	1616 KENSINGTON AVE
Line 2 Street Address		
Marker of address line 2 suppression	N	N
City	BROOKLYN	BUFFALO
State	NY	NY
Zip Code	11229	14215
Claims based hospital affiliation CCN 1	330214	330078
Claims based hospital affiliation LBN 1	NYU HOSPITALS CENTER	SISTERS OF CHARITY HOSPITAL OF BUFFALO NEW YORK
Claims based hospital affiliation CCN 2		330005
Claims based hospital affiliation LBN 2		KALEIDA HEALTH
Claims based hospital affiliation CCN 3		
Claims based hospital affiliation LBN 3		
Claims based hospital affiliation CCN 4		
Claims based hospital affiliation LBN 4		
Claims based hospital affiliation CCN 5		
Claims based hospital affiliation LBN 5		
Professional accepts Medicare Assignment	Y	Y
Participating in eRx		Y
Participating in PQRS		Y
Participating in HER		Y
Received PQRS Maintenance of Certification Program Incentive		
Participated in Million Hearts		

Fig. 6 Organization of data in the National Downloadable file of healthcare professionals from CMS. The shaded column shows the names of the fields for the data. The next two columns show the data for two randomly selected healthcare practitioners. There is data for 895,431 unique practitioners across the USA in this file. This is being done for illustrative purposes only and to describe our method in detail.

Provider Number	330214	330078
Hospital Name	NYU HOSPITALS CENTER	SISTERS OF CHARITY HOSPITAL
Address	550 FIRST AVENUE	2157 MAIN STREET
City	New York	Buffalo
State	NY	NY
ZIP Code	10016	14214
County Name	NEW YORK	ERIE
Unweighted Normalized Clinical Process of Care Domain Score	75.45454545	70
Weighted Clinical Process of Care Domain Score	15.09090909	14
Unweighted Patient Experience of Care Domain Score	32	34
Weighted Patient Experience of Care Domain Score	9.6	10.2
Unweighted Normalized Outcome Domain Score	84	70
Weighted Outcome Domain Score	25.2	21
Unweighted Normalized Efficiency Domain Score	10	30
Weighted Efficiency Domain Score	2	6
Total Performance Score	51.89090909	51.2

Fig. 7 The format of the data for performance scores is shown in this figure. The shaded first column shows the names of the fields. Two sample columns of data are shown next. Note that the provider number in the second column, 330,214 corresponding to NYU Hospitals Center, and highlighted in yellow, matches the provider number in the second column of Fig. 6. Similarly the provider number in the third column, 330,078 for Sisters of Charity Hospital, and highlighted in green, is also present in Fig. 6. These fields are used to join the tables. For our correlation analysis, we focus on the last row, containing the "Total performance score" generated by CMS. There are 3089 unique hospitals represented in this file

MEDICAL SCHOOL NAME	RANK
HARVARD MEDICAL SCHOOL	1
UNIVERSITY OF CALIFORNIA, San Francisco	2
JOHNS HOPKINS UNIVERSITY SCHOOL OF MEDICINE	3
UNIVERSITY OF PENNSYLVANIA SCHOOL OF MEDICINE	4
UNIVERSITY OF WASHINGTON SCHOOL OF MEDICINE	5
UNIVERSITY OF CALIFORNIA, Los Angeles	6
UNIVERSITY OF MICHIGAN MEDICAL SCHOOL	7
UNIVERSITY OF NORTH CAROLINA AT CHAPEL HILL SCHOOL OF MEDICINE	8
UNIVERSITY OF PITTSBURGH SCHOOL OF MEDICINE	9
STANFORD UNIVERSITY SCHOOL OF MEDICINE	10
MOUNT SINAI SCHOOL OF MEDICINE OF CITY UNIVERSITY OF NEW YORK	41

Fig. 8 This shows the top 10 ranked medical schools. The Mount Sinai School of Medicine of City University of New York with rank 41 is also shown as this data is used to illustrate a database join

NPI	1245439843
PAC ID	7719077189
Professional Enrollment ID	I20071221000416
Last Name	WALFISH
First Name	MENACHEM
Medical school name	MOUNT SINAI SCHOOL OF MEDICINE OF CITY UNIVERSITY OF NEW YORK
Medical school rank	41
Claims based hospital affiliation CCN 1	330214
Claims based hospital affiliation LBN 1	NYU HOSPITALS CENTER
Total Performance Score	51.89090909

Fig. 9 This figure illustrates the data joined from three separate tables containing practitioner information, hospital information and medical school information. The color coding reflects the relation between the fields in this figure and the fields in Figs. 6, 7 and 8

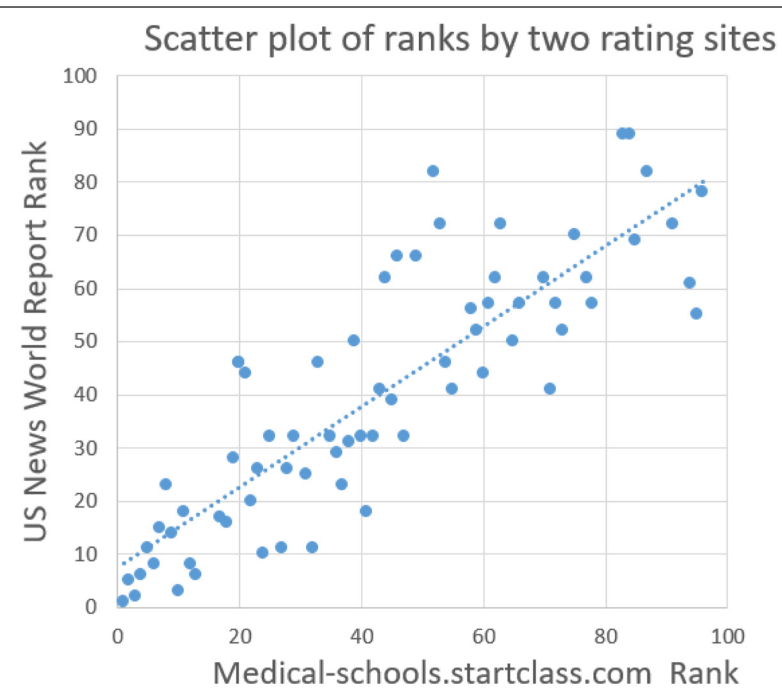


Fig. 10 This figure shows the relation between medical college ranks obtained from US News and World Report (y-axis) and the ranks obtained from medical-schools.startclass.com (x-axis). The scatterplot shows a near linear relationship, with most points clustered along the dotted trendline. The correlation coefficient is R = 0.85. The *p*-value is less than 0.001, indicating that the correlation coefficient is statistically significant

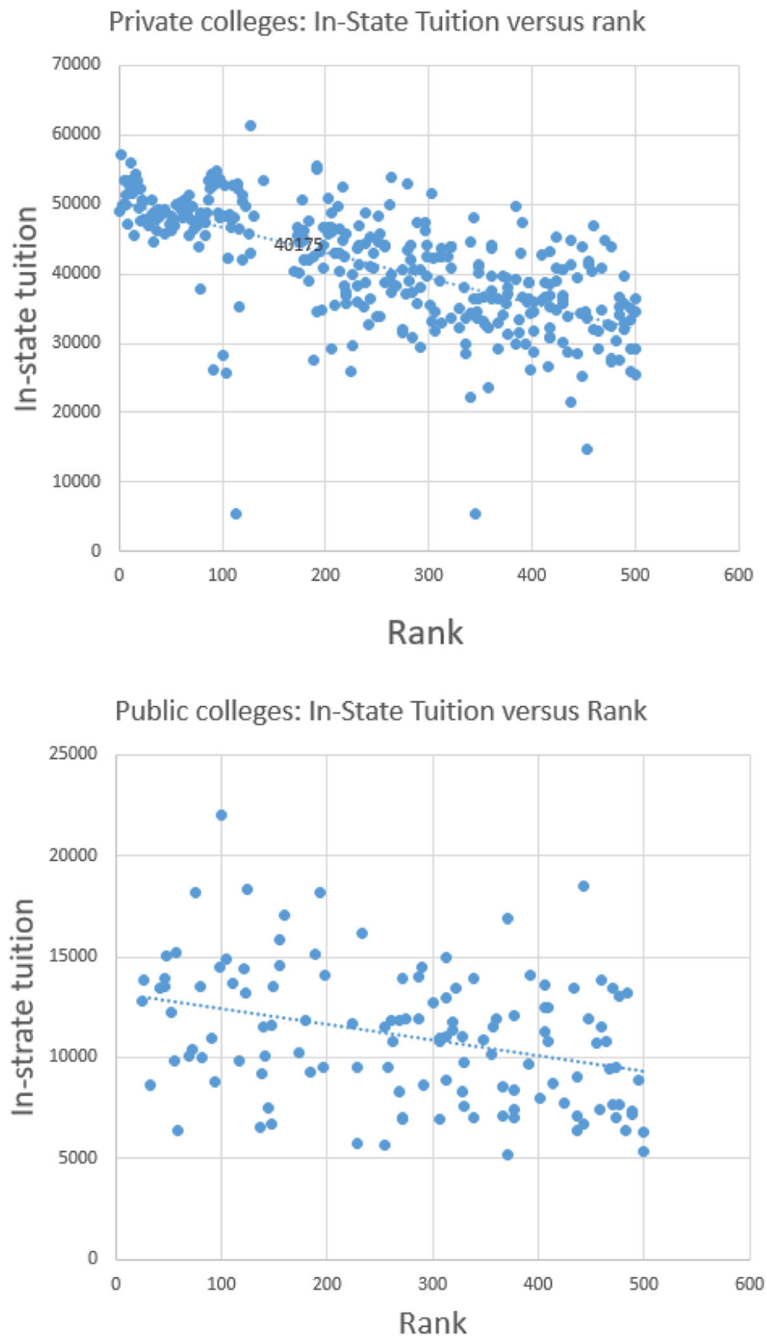


Fig. 11 Comparing the distributions of rank versus costs for private and public colleges. The Pearson correlation between the rank of a college and its in-state tuition was − 0.36 ($p < 0.005$), indicating that higher-ranked colleges were more expensive. We segmented the colleges into the categories of private or public. The Pearson correlation between rank and in-state tuition was − 0.65 ($p < 0.005$) for private colleges, and − 0.34 ($p < 0.005$) for public colleges

contribute to make our methodology replicable and independently verifiable by researchers and concerned citizens. Our approach has the potential to transform the healthcare research landscape through data and code sharing. This could create a new model for conducting healthcare research.

Appendix

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Availability of data and materials
Will be provided at www.github.com/fdudatamining

Authors' contributions
The authors contributed equally to all parts of this study, including data gathering, analysis and writing.

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors state that they have no competing interests.

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