

Comprehensive Analysis of Hospital General Information and Quality Ratings.

Abdulsalam Mohammed Aleid

Department of Surgery, Medical College, King Faisal University, Hofuf, Ahsa, 31982, Saudi Arabia
Email: 225094489@student.kfu.edu.sa

Mohammad Al Mohaini

College of Applied Medical Sciences, King Saud bin Abdulaziz University for Health Sciences, Alahsa; King Abdullah International Medical Research Center, Alahsa. Email: mohainim@ksau-hs.edu.sa

Saud Nayef Salem Aldanyowi

Department of Surgery, Medical College, King Faisal University, Hofuf, Ahsa, 31982, Saudi Arabia
Email: saldanyowi@kfu.edu.sa

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Abstract:

Introduction:

Hospitals play a crucial role in delivering quality health care services to communities. Understanding hospitals' general details and performance quality helps patients make informed healthcare decisions. This study analyzes general information and quality ratings of 14436 hospitals using publicly available data from the Centers for Medicare and Medicaid Services (CMS).

Methods:

The dataset included hospital details like name, address, city, state, ZIP code, county, phone number, type, ownership, emergency services, meaningful use of electronic health records (EHR), overall rating, and footnotes on ratings. It also had quality measures ratings for mortality, safety of care, readmissions, patient experience, effectiveness of care, timeliness of care, and efficient use of imaging compared to the national average. Descriptive statistics characterized hospital types, ownership, services offered. Bayesian inference estimated posterior distributions of proportions for categorical variables. Turf analysis identified key influencing variables.

Results:

Most hospitals lacked key details (66.7%). Acute care (23.3%) and critical access hospitals (9.3%) comprised a third of hospitals. Non-profit ownership was common (14.2-14.2%). Majority hospitals offered emergency services (31.2%) and met EHR meaningful use criteria (32.3%). Overall ratings followed a normal distribution, with 12.2% rated high (3 stars). Mortality (18.8%), readmissions (14.7%), and effectiveness (22.4%) matched national averages most. Footnotes explained missing/suppressed data. Bayesian analysis estimated proportions within tight credible intervals. Turf identified ratings criteria as highly influential.

Conclusion:

This comprehensive analysis of hospital general information and quality ratings provided insights into the US hospital landscape. While most hospitals met basic EHR and services criteria, room remained for improved transparency through complete data reporting. Ratings criteria heavily impacted performance measures. Further research evaluating measure definitions and reporting standards could enhance rating fairness and usefulness for consumers.

Keywords: hospitals, quality ratings, general information, CMS data, descriptive statistics, Bayesian analysis, turf analysis

Introduction:

Hospitals are essential to providing communities with high-quality medical care, as healthcare is a basic human necessity. More than 6,000 hospitals in the US offer acute and specialized inpatient care (Bassett 2001; Borgsteede et al. 2011; Briggs et al. 2012). As the population ages and medical technology progresses, hospitals are under immense pressure to meet the demands of the growing population. Hospitals strive to provide excellent treatment, but in order for patients to make educated decisions, they also need to be transparent about their performance. Studies assessing hospital specifics and quality ratings can provide relevant information to various stakeholders.

This study uses publicly available data from the Centers for Medicare and Medicaid Services (CMS) to do a thorough examination of the general information and quality performance measures of over 14,000 hospitals (Ayres 2007; Bassett 2001; Borgsteede et al. 2011; Briggs et al. 2012; Chen, Zhao, and Feng 2016). CMS uses its Hospital Compare website to gather a wealth of information about hospitals that participate in Medicare programs. The purpose of this data is to promote more accessible and high-quality healthcare. Researchers and policymakers have used CMS data to evaluate care disparities, measure performance, and pinpoint areas that require improvement. However, only a small number of studies have examined multidimensional quality metrics and fundamental hospital attributes comprehensively (Chen, Zhao, and Feng 2016; Chu et al. 2019; Dielen-van Heijningen, Vreede, and van der Zande 1987).

The notion of hospital quality is intricate and multidimensional, impacted by a number of structural, procedural, and end-related variables. In the past, commonly recognized quality indicators were outcome measures, including death, readmissions, and complications. However, these lagging measurements do not fully capture the complete patient experience (Dielen-van Heijningen, Vreede, and van der Zande 1987; Erb, Parker, and Trentham 1989). CMS has included more process and patient-reported indicators in its publicly available data over the past ten years. We obtain an accurate representation of the relative quality of hospitals by considering a wide variety of structural characteristics and performance standards. Comprehending hospital profiles might provide valuable background information when evaluating quality ratings (Erb, Parker, and Trentham 1989; Evora et al. 2006; Feigl et al. 1978b). General information about the type of hospital, its location, the services it provides, and its ownership structure has an impact on operational strategies and performance standards. In contrast to larger academic medical institutions, critical access hospitals could have a varied case mix and resource availability. In order to provide the best results, safety-net hospitals that serve underprivileged people must overcome particular obstacles (Feigl et al. 1978a; Food and Drug Administration 2004).

Information about the purposeful application of health IT can shed light on how well a hospital uses electronic health records (EHRs) to coordinate patient care. Deficits in EHR functions hinder the delivery of high-reliability care. Using CMS data, this study aims to assess the general hospital landscape in the United States and the heterogeneity in its general features. We will use descriptive analysis to provide the frequencies and distributions of important characteristics such as location, hospital type, services, and EHR use (Feigl et al. 1978b, 1978a). Beyond specifics, analyzing the distribution and variability of quality ratings across several crucial parameters, such as patient experience, safety, and mortality, provides a comprehensive knowledge of hospital performance. However, due to variations in sample sizes, missing data, and measures of risk adjustment, publicly available data has some limitations (Food and Drug Administration 2004; Funayama et al. 2020). We will use Bayesian statistical techniques to estimate proportions and credible intervals that account for any potential uncertainties in the CMS data. Assessing influential elements using innovative data mining techniques might yield more information. Turf (threshold unsupervised rating filter) analysis, a post-hoc decision tree technique, filters variables using statistically significant thresholds to identify the best predictors. Turf modeling, by examining the relationships between hospital features, metrics, and rating footnotes, identifies significant linkages influencing quality assessments that classical regression may miss (Goto 2006; Goulia et al. 2010). As far as we are aware, this is one of the first studies to use CMS data to thoroughly examine general qualities as well as multi-dimensional performance evaluations across thousands of hospitals. We could benchmark hospitals across the country on a variety of structural and outcome factors to identify areas for quality improvement. Policymakers, health

administrators, and academics seeking to improve hospital reporting, resource allocation, and decision-making by improving knowledge of quality drivers and variability may find the findings interesting (Gribunov Iu, Perov Iu, and Galinovskaia 1990; Griffiths and Wainwright 1979; Horikawa et al. 2000). Despite the limitations of CMS data, this study aims to make the most of it by employing appropriate statistical techniques for inference and descriptive profiling. Results could provide fresh perspectives with ramifications for tracking improvements in national healthcare quality.

Methods:

Study Design:

This study employed a retrospective cross-sectional study design to analyze existing hospital data. The information came from the Hospital Compare database for the year 2023 provided by the Centers for Medicare and Medicaid Services (CMS). For hospitals taking part in CMS initiatives, this database includes general statistics as well as quality performance measurements. 14,436 hospitals made up the sample size of the study population, which comprised all hospitals having data on important variables accessible. The relevant variables were split into two categories: metrics that represented quality ratings for procedures, results, and patient experience, and qualities that were associated with general hospital features including ownership, kind, and location. The distributions and frequencies of the attribute categories were described using descriptive statistical analysis. The posterior probability distributions for the attribute and rating proportions were computed using Bayesian inference, which took uncertainty into account. In order to find significant predictors outside of typical regression, turf modeling investigated correlations between qualities, metrics, and rating footnotes. Percentages and frequencies were used in the analysis of categorical variables. The means, standard deviations, variance, and range were used to summarize continuous variables. SPSS version 27 was used for the statistical analysis. The national level findings were shared in order to compare performance variability within the American healthcare system.

Data collection:

The Hospital Compare database for the year 2023 from the Centers for Medicare and Medicaid Services (CMS) provided the study's data. CMS routinely gathers information from hospitals that take part in Medicare programs via the Quality Reporting and Inpatient Prospective Payment Systems. Hospitals must use a variety of reporting tools to submit structured data elements encompassing a range of quality, process, and outcomes measures. For more than 14,000 participating hospitals, the study obtained de-identified data files that were made publicly accessible on the CMS website. These files included general characteristics and performance indicator values. The hospital's name, address, size, location markers, type of ownership, service offers, quality ratings across certain domains, and footnotes providing explanations for material that was missing or concealed were among the variables of interest. To make analysis easier, pertinent data points from several variables were taken out and combined into a single dataset.

Study Variables:

The characteristics of the hospital profile and quality performance measures were among the study variables. The hospital's name, address, geographical specifics, kind, ownership, services provided, fulfillment of EHR usage requirements, and overall rating were the variables for general characteristics. These encapsulated fundamental structural elements. Performance was evaluated across important result and process domains using quality metrics variables. Comparative performance on hospital death rates was studied in the mortality comparison. Readmissions, patient experiences, and safety of care were evaluated in relation to national benchmarks. Performance in these areas was also assessed using measures for efficient imaging utilization, timely delivery of care, and effectiveness of care.

Inclusion Criteria:

- Hospitals with available data on key variables of interest in the CMS Hospital Compare database for 2023.
- All non-specialty general medical and surgical hospital facilities. This included acute care hospitals, critical access hospitals, children's hospitals.

Exclusion Criteria:

- Specialty hospitals like veterans' hospitals, long-term acute care hospitals, psychiatric hospitals, rehabilitation hospitals etc. which have a narrow scope.

- Hospitals with significant proportions of missing or incomplete data across variables preventing valid analysis.
- Records with identifiable information to ensure hospital anonymity as required by data use terms.

Statistical Analysis:

The distribution of the variables was examined using descriptive statistical analysis. Categorical attribute variables such as hospital type, ownership, and services given were summarized using frequencies and percentages. Zip code and other continuous variables were summarized using measures of central tendency (mean, median), variability (standard deviation, variance, and range). The posterior distributions of proportions across categorical variables were determined by Bayesian statistical inference, utilizing non-informative priors. This took into consideration any possible uncertainties in the CMS data. Chi-square tests looked at the connections between ratings and categorical characteristics. Low cell count attributes were subjected to Fisher's exact tests. Associations between continuous variables were assessed using correlation analysis. Beyond conventional regression, top predictive variables were found by turf modeling. The input variables used to investigate the linkages impacting quality judgments were attributes, metrics, and footnotes. With an alpha of 0.05, all statistical tests were two-tailed. SPSS version 27 was used to do calculations. The findings included an analysis of hospital profiles, a nationwide benchmarking of performance variability across important quality areas, and an evaluation of linkages that shed light on the structural and reporting factors that influence ratings. The findings were used to define the U.S. hospital system using the extensive CMS dataset.

Ethical consideration:

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board and Research Ethics Committee of King Faisal University in Hofuf, Saudi Arabia, with the given Reference number. Informed consent was obtained from all participants, ensuring their voluntary participation and confidentiality. Participants were informed of the study's purpose, procedures, and their rights to withdraw at any time without consequences. Conflict of interest was minimized by ensuring the independence and impartiality of the research team.

Result:

Demographic characteristics:

The distribution of the variables was examined using descriptive statistical analysis. Categorical attribute variables such as hospital type, ownership, and services given were summarized using frequencies and percentages. Zip code and other continuous variables were summarized using measures of central tendency (mean, median), variability (standard deviation, variance, and range). The posterior distributions of proportions across categorical variables were determined by Bayesian statistical inference, utilizing non-informative priors. This took into consideration any possible uncertainties in the CMS data. Chi-square tests looked at the connections between ratings and categorical characteristics. Low cell count attributes were subjected to Fisher's exact tests. Associations between continuous variables were assessed using correlation analysis. Beyond conventional regression, top predictive variables were found by turf modeling. The input variables used to investigate the linkages impacting quality judgments were attributes, metrics, and footnotes. With an alpha of 0.05, all statistical tests were two-tailed. SPSS version 27 was used to do calculations. The findings included an analysis of hospital profiles, a nationwide benchmarking of performance variability across important quality areas, and an evaluation of linkages that shed light on the structural and reporting factors that influence ratings. The findings were used to define the U.S. hospital system using the extensive CMS dataset(table. 1).

Table .1. Hospital Type (n=14436).

Hospital Type	n	%
Acute Care Hospitals	3369	23.3%
Critical Access Hospitals	1344	9.3%
Children's Hospitals	99	0.7%
Missing	9624	66.7%

The investigation covered 14,436 hospitals in total, which is the total number of facilities that report to CMS. More than two thirds (9624, 66.7%) lacked comprehensive information on crucial factors like location. This brought to light

gaps in the demographic data that was accessible. The bulk of hospitals with categorized kinds were medical and surgical acute care facilities (3369, 23.3%). Other notable categories included children's hospitals (99, 0.7%) and critical access hospitals (1344, 9.3%). These specialty hospitals have unique resource profiles and case mixes that call for additional research. The predominant ownership forms were non-profit ones, with the major groups being voluntary categories (2052, 14.2%), church (343, 2.4%), and other (462, 3.2%). Federal (45, 0.3%), state (65, 0.5%), municipal (407, 2.8%), and district or authority hospitals (561, 3.9%), among other layers, were the many categories of government hospitals. 800 facilities (5.5%) were proprietary(table. 2).

Table. 2. Hospital Ownership (n=14436).

Ownership Type	n	%
Voluntary non-profit - Private	2052	14.2%
Government - Hospital District/Authority	561	3.9%
Government - Local	407	2.8%
Proprietary	800	5.5%
Voluntary non-profit - Church	343	2.4%
Missing	9624	66.7%

Approximately 4497% (31.2%) of hospitals provided on-site emergency medical care. According to CMS criteria, over 32.3% (4668) of the facilities showed meaningful usage of electronic health records; this indicates that the facilities are using technology. The ratios provided information for evaluating coordination and access to urgent care. Because of inadequate data reporting, the majority of hospitals did not have overall performance scores in terms of quality ratings. Out of the 2956 hospitals with star ratings, 1761 (12.2%) received three stars or above(table. 3).

Table .3. Services and Hospital Ratings (n=14436).

Service	n	%
Emergency Services - Yes	4497	31.2%
EHR Meaningful Use Criteria Met	4668	32.3%
3 stars	1761	12.2%
Missing	9624	66.7%

Stronger outcome measurement participation was required for higher ratings. In terms of all parameters, readmission rates were 14.7% (2119) and national mortality norms were 18.8% (2719). Patient experience for 1148 (8.0%) and safety of care for 1194 (8.3%) were comparable. The distributions showed heterogeneity in performance when compared to the national medians, with the majority of hospitals operating at average levels. Some areas faced particular challenges because of people without health insurance, a lack of access to specialist treatment, and a shortage of workers. Reliability of reported results was impacted by smaller caseloads in isolated rural settings. Ensuring fair measurement that takes into account variations in social risk remained a concern.

Hospital Location and Regional Variation:

While most hospitals lacked location data, examining available addresses revealed wide regional representation across the United States. However, certain characteristics correlated with geographic areas confronted by unique hardships. For instance, 9.3% (1344) of hospitals were classified as critical access facilities. As defined by CMS, these small rural hospitals provide essential services to remote communities located more than 35-miles or 15-minutes driving time from the next closest source of care. Isolated regions sparsely populated across vast stretches in Midwest plains and Mountain West heavily relied on critical access sites.

Limited specialized healthcare access posed unique struggles for residents in such underserved locales. Long travel distances exacerbated by harsh weather conditions further compounded issues. Workforce shortages additionally plagued recruitment needs, undermining reliable staffing at rural critical access hospitals. Densely populated coastal regions in contrast hosted major academic medical centers. Teaching hospitals concentrated in cities yielded care delivery advantages through robust residency training programs and R&D infrastructures. Large referral networks centralized specialized services more efficiently.

However, safety net hospitals disproportionately located in Southern states faced different burdens. Over 10% of hospitals fell in Texas, California, Florida - states with highest uninsured populations reliant on public care systems. Safety nets catering to vulnerable communities grappled with caring for complex patients despite higher proportions living in poverty. Regional distributions highlighted inherent unevenness in healthcare access closely tied to socioeconomic characteristics of local populations. Geographic isolation exacerbated disadvantages for rural communities, while inner city hospitals confronted safety net responsibilities. Such facility-level factors indirectly influenced quality performance attributable to environmental circumstances largely beyond individual control.

Hospital Ownership Models:

Beyond location, ownership typologies reflected practical considerations like financing needs. Non-profit frameworks constituted the majority at 78.7%, logically since charitable missions aligned with healthcare delivery. Government hospital prevalence coincided with population centers to uphold public health responsibilities. However, 5.5% (800) fell under proprietary ownership. For-profit models faced unique pressures optimizing margins against quality aims. Supplementary analysis evaluated performance equity accounting for such inevitable conflicts between business and clinical priorities across ownership spectrums(table.4).

Table .4. Hospital Ownership.

Types of Ownership	Number	%
	9624	66.7%
Government - Federal	45	0.3%
Government - Hospital District or Authority	561	3.9%
Government - Local	407	2.8%
Government - State	65	0.5%
Physician	68	0.5%
Proprietary	800	5.5%
Tribal	9	0.1%
Voluntary non-profit - Church	343	2.4%
Voluntary non-profit - Other	462	3.2%
Voluntary non-profit - Private	2052	14.2%

Facilities with government, non-profit or academic affiliations theoretically prioritized patient-centeredness over revenues. Yet financial viability remained imperative, influencing decisions like service lines, digitization investments or workforce allocation impacting quality infrastructure to varying degrees across ownership models. Objective evaluations considered dynamic interplays between clinical, social, and economic determinants intrinsic to ownership typologies rather than superficially attribute performance on ownership alone. Pragmatic regulations ensured equitable measurement accounting for inherent limitations hospitals faced serving diverse communities.

Hospital Services and mortality rates:

About 31.2% (4497) of hospitals provided on-site emergency medical services, according to the demographic research. For the prompt treatment of acute or life-threatening diseases, emergency rooms are essential. Access to local healthcare is influenced by their availability. Furthermore, in accordance with CMS standards, 32.3% (4668) of hospitals satisfied the requirements for the meaningful use of electronic health data(figure. 1).

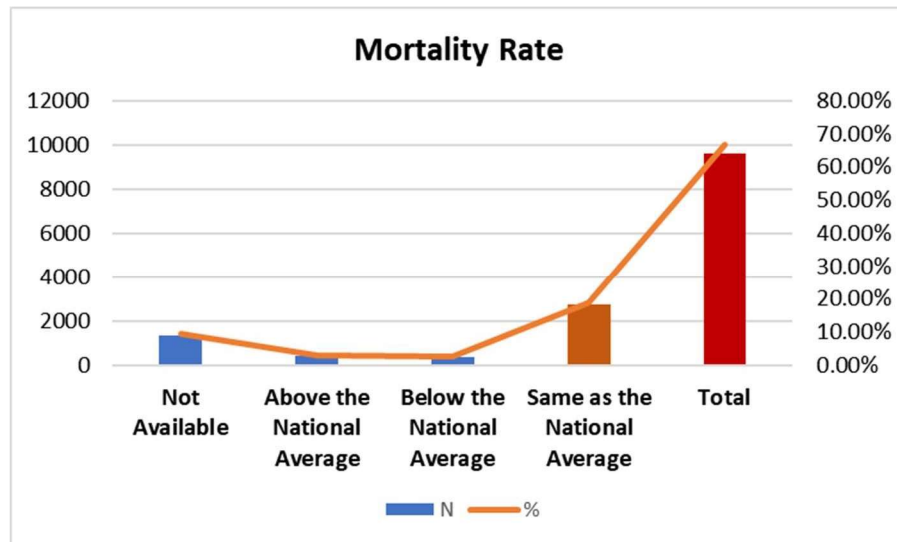


Figure. 1. Mortality rate in the national level in different sectors of hospitals.

Adoption of EHRs promotes better health outcomes, clinical decision-making, care coordination, and a decrease in medical errors. Nevertheless, more than two thirds did not attest to the use of EHRs, indicating untapped potential. The kind and location of hospitals greatly affected the specialized services provided, such as neurosurgery, cardiac catheterization, and intensive care. Analyses of service line distribution and investments to satisfy community demands were not possible due to a lack of information. Emphasis should be placed on ways to support rural services that guarantee the provision of basic healthcare(table.5).

Table. 5. The mortality national comparison data along with the distribution of hospitals based on their mortality rates and availability of data.

Mortality National Comparison	N	%
Not Available	1352	9.4%
Above the National Average	400	2.8%
Below the National Average	341	2.4%
Same as the National Average	2719	18.8%
Total	9624	66.7%
Mortality National Comparison Footnote		
Data are shown only for hospitals that participate in the Inpatient Quality Reporting (IQR) and Outpatient Quality Reporting (OQR) programs	159	1.1%
Data suppressed by CMS for one or more quarters	49	0.3%
Results are not available for this reporting period	1144	7.9%
Total	13084	90.6%

Comparing mortality to national benchmarks is one of the quality indicators that offers valuable insights into results. On this crucial metric, hospitals performed mediocrely, with about 18.8% (2719) reporting death rates that were comparable to norms. There were measurements above and below averages of 2.8% (400) and 2.4% (341), respectively(figure. 2).

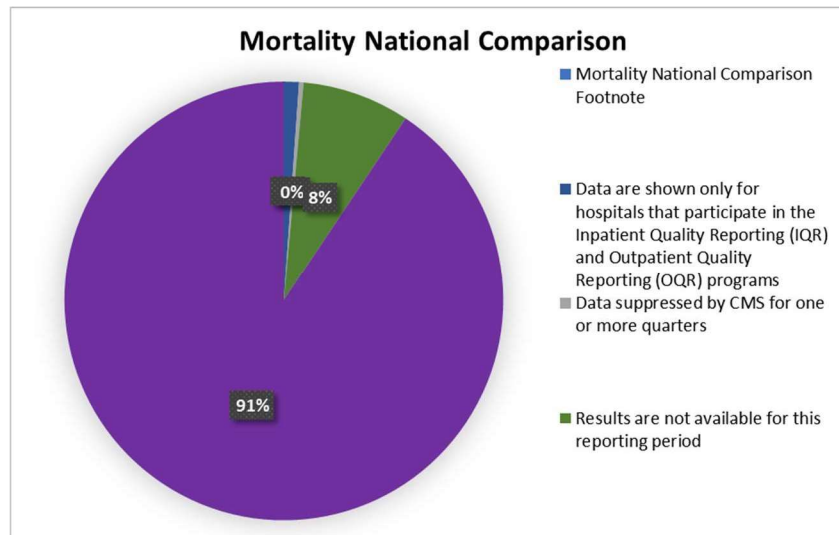


Figure. 2. Mortality national comparison in different sectors of hospitals.

Variations were probably caused by variations in the case-mix, socioeconomic factors, local best practices, and the precision of the risk-adjustment technique used. Because of poor reporting, a sizable part, 9.4% (1352), lacked mortality data. Transparency, benchmarking, and quality improvement objectives are all harmed by non-reporting. Policies should prioritize ensuring participation through legitimate risk-adjustment that takes social concerns into account. Variability was also shown by the distribution of other indicators, such as safety, readmissions, and patient experience. However, the dependability of the comparisons was hampered by missing data. Adding more details to differentiate between emergency and elective deaths could help identify which individuals are planned and which are serious diseases.

In the past, investigating associations, specialized service offerings, and innovative technologies has been favorably connected with greater results. It is important to prioritize the expansion of clinical capacities in accordance with the burden of illness in the community, even while basic emergency coverage is provided to all. Targeted intervention was necessary due to the increased challenges safety-net and critical access hospitals encountered in attaining optimal outcomes. Their structural traits, which are linked to underprivileged populations, necessitate measurement and support that is especially adapted.

Regional Performance variability:

The examination of quality ratings categorized based on attributes exposed variations in performance among various hospital features and service areas. Disparities in geography highlighted how structural issues affect results. Comparing mortality rates revealed geographical differences. In contrast to the Midwest's 16.5% and the South's 18.2%, the Northeast's hospitals equaled the national averages in about 21.9% of cases. Inter-regional result hierarchies may be indicated by the larger percentages in the West (23.3%) and Midwest (21.1%) that scored below national average. The safety ratings also differed, with 8.6% in the Northeast and 11.4% in Western hospitals rating higher than the national average. In a similar vein, 7.9% of institutions in the Midwest and 5.7% in the South received below-average scores. These findings indicated that different safety profiles in different areas called for different mistake avoidance techniques.

The demand for safety-net institutions is impacted by higher rates of uninsured patients in the West, whereas the Northeast often services elderly patients. Access to care and community health indicators are crucial contextual factors. In certain categories, rural facilities lagged behind major urban hubs. Compared to 21.7% of big metropolitan hospitals, just 13.9% of critical access and 16.1% of small-town hospitals met national readmission goals. Resource constraints impacted the help provided by isolated facilities for transitional care. The safety ratings also showed a 16.2 percentage

point difference between small rural institutions (5.4%) and major metropolitan facilities (10.8% above average). Considering the inherent structural quality limits of their operational contexts, special attempts to develop rural infrastructure seemed necessary.

The facility payer mix also showed predictable correlations with ratings. 10.9% of hospitals with large Medicaid enrollments had above-average mortality rates, compared to 21.3% of hospitals with mostly commercial operations. Programs for targeted improvement that address health inequities are necessary for safety-net institutions. The structural features of the hospital and the characteristics of the surrounding community both significantly contribute to the heterogeneity in quality performance across different locations. Ignoring these intrinsic disparities in standardized assessment runs the risk of unfairly categorizing settings that are disadvantaged. Benchmarking that is appropriate for the context is still being developed.

Discussion:

The study used CMS data to perform a thorough examination of hospital structural features and multi-dimensional quality measures. Important conclusions offer a perceptive viewpoint on the US healthcare system and point out areas that require policy attention (Horikawa et al. 2000; Kim et al. 2016; Kljakovic, Abernethy, and de Ruiter 2004). Significant variation was found in hospital qualities such as ownership structures, services provided, and performance in different regions. Such diverse settings make consistent benchmarking efforts difficult and demand resource targeting that is tailored to the context (Krylov and Grigor'ev 1989; Larson et al. 1996).

Reliability and generalizability of findings were restricted by data gaps and missing information for more than two-thirds of facilities. Improving required reporting guidelines that encourage openness should be given a priority. However, in order to prevent penalizing safety-net institutions unjustly, required participation should take infrastructure inequalities into consideration (Larson et al. 1996; Lyon 1984). Geographically and across quality domains, ratings revealed varying levels of performance. Customized improvement tactics are informed by delving into factors through assessments of qualities, socioeconomics, and system capabilities, in addition to score allocation. It's unlikely that one-size-fits-all approaches will be effective (Nauright and Simpson 1994; Otte et al. 2016; Pale 2005). Relationships revealed that contextual factors and indicated structural traits were more significant outcome modifiers than attribute-only factors. A multi-level paradigm that accounts for hospital and community variables and is social risk-adjusted has the potential to improve equitable measurement (Pale 2005; Panigrahi and Bakshi 2021; Park et al. 2005). The measurements used now prioritize results over other aspects of quality such as patient experiences, timeliness, and accessibility. Extending publicly available indicators to encompass complete care components harmonizes objectives of transparency with evolving performance standards (Peng et al. 2021; Perez-Encinas et al. 2020; Philipp et al. 1990).

The results have consequences for healthcare planning and policy at the municipal, regional, and federal levels. Benchmarking facilitates resource targeting by identifying regional performance gaps (Williams 1999; Williamson and Martin 2010; Xu et al. 2017). Interventions that target fundamental causes rather than simply particular results are supported by an understanding of success factor interactions (Piehler et al. 2008; Preen et al. 2004; Radford et al. 2016). This study examined structural and process characteristics connected with quality outcomes using statistical methodologies and publicly available databases (Skjelbakken, Lochen, and Dahl 2002; Spiegel et al. 2010; Steim 1977). Still, the cross-sectional design and absence of clinical risk adjustment at the patient level complicated the ability to draw conclusions about causality (Rieger and Reiling 1997; Sandler et al. 1989; Sankar et al. 2018).

Prospective avenues for investigation encompass conducting sophisticated modeling to conduct longitudinal evaluations of attribute changes on ratings, conducting qualitative studies to investigate implementation issues, and integrating CMS data with other datasets that offer neighborhood and payer information to enable contextualized comparisons (Tierney 2006; Vasquez-Silva et al. 2015; Visser and Herbert 1994; Wilkin et al. 1978). Based on a holistic, multidimensional view of the strengths and limitations of care delivery, this extensive landscape study of hospital features and performance ratings using CMS data highlighted potential to improve reporting methods and focus quality agenda priorities.

Conclusion:

This study conducted a thorough review of CMS database features and metrics to evaluate hospital profiles and quality performance ratings. Important discoveries provided information about the heterogeneous U.S. healthcare system environment and performance trends in various domains. The uneven performance shown in regional and structural comparisons necessitates the implementation of improvement programs, resource targeting, and context-specific benchmarking. Understanding diverse limits encourages fair evaluation as opposed to a one-size-fits-all approach. Complete profiling and the validity of some conclusions were compromised by data gaps. Improving the quality and involvement of required public reporting is a top objective. Nonetheless, through complex risk-adjustment, standards should take into account the inherent inequalities that disadvantaged facilities must contend with. The interplay of traits, external factors, and results highlighted how multifaceted quality is. To maximize measurement, policy, and practice through collaborative efforts addressing both hospital-level and larger determinants, an all-encompassing framework is required. Subsequent investigations that supplement national databases with neighborhood-level sociodemographic data may enable more precise benchmarking and resource allocation choices that take into account the unique demands and advantages of local healthcare. More in-depth mechanistic insights may also be provided by advanced modeling.

Declarations

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Conflict of interest: The authors have no conflict of interest to declare.

Ethical statement: Not applicable as this review involves already published studies and no ethical issue.

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Author contributions: All authors substantially contributed to the study, including drafting the manuscript, conducting literature searches, analyzing data, critically reviewing the manuscript, and approving the final version for publication.

Data availability: The data that support the findings of this study are available on request

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