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Statistical Computation and Its Application in Hospital Performance Management: A Performance Appraisal Perspective

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Abstract

Assessing hospital performance during quality improvement initiatives relies heavily on statistical methodologies aimed at benchmarking. This multi-institutional study evaluates established statistical approaches for their applicability in improving healthcare quality. Using a dataset encompassing 48,521 patients undergoing craniotomy surgery from 2019 to 2023 across 180 hospitals, 6 statistical techniques were analyzed. Non-contraction methods included indirect standardization without hospital effects, with fixed effects, and direct standardization with fixed effects. Contraction methods comprised direct standardization with random effects, indirect standardization with random effects, and Exponential Smoothing methods. Adjusted rates, rankings, and performance outliers are the main emphasis of this study, which evaluates hospital performance concerning the rate of operation deaths and severe complications or deaths among approaches. Contraction methods significantly reduced inter-hospital variation in death rate(adjusted: 1%2%; observed: 0%-10%) and severe complications or death (observed: 3%-35%; adjusted: 7%-17%). Hospital rates were effectively brought closer to the collective mean using these techniques. Direct standardization with hospital random effects resulted in significant changes in death rate quintile rankings for 17% to 39% of hospitals when compared to fixed effects. Indirect standardization with random effects revealed no performance outliers for death rates in compact and moderate-sized hospitals, but logistic and fixed effect approaches revealed outliers. The choice of statistical approach has a considerable impact on hospital rankings and the identification of performance outliers. These insights are critical for appropriately evaluating the hospital's effectiveness in quality improvement initiatives.

Keywords: Hospital performance, Statistical methods, Quality improvement, Contraction methods, Hospital volume terciles.

Introduction

Effective hospital management is crucial for patient success and efficient healthcare service delivery. Integrating statistical computation with performance management can significantly improve various aspects of healthcare delivery [1]. High-performing management is essential in maintaining a good standard of patient services while at the same time being financially sustainable. Current research has placed a focus on the use of contemporary quantitative methods to extract useful information from hospital records. For instance, big data analytics has been discussed to redesign the management of healthcare by embracing the synthesis and evaluation of large and intricate data sets to produce better decisions [2]. Furthermore, the role of change in healthcare organizations has also been highlighted in physicians' performance and the outcomes for patients. Among the theoretical frameworks, transformational leadership qualities can greatly shape the practice of healthcare by improving organizational climate and motivational level among healthcare professionals [3].

Hospital quality measures are also dependent on financial performance which is a major aspect of hospital performance. The studies show that hospitals that pay attention to quality improvement experience a trend of favorable financial effects. For instance, a study showed that establishing quality measures including patient safety and satisfaction significantly affects the profitability of the hospitals [4]. In addition, one of the vital tools in performance management is patient satisfaction surveys. A high response rate and positive feedback from patients show how well the hospital is providing service delivery and its operations function. A cross-sectional survey in Swiss Hospitals showed a positive association between patient satisfaction and hospital performance [5].

One more area where statistical computation becomes quite helpful is human resource management in healthcare. Big data analytics of workforce management could enhance the utilization of HRM practices for better management of hospitals and for providing improved care to patients [6]. In addition, the use of technology in hospitals, especially through using electronic health records (EHRs) and other tools in managing the hospitals' performances, contributes to the effectiveness of performance measures. Several works have also linked EHR systems to other facets like; improved patient outcomes and operational performances [7]. In conclusion, the use of statistical computation in the management of hospital performance continues to adapt as it offers a broad technique towards measuring the continually evolving hospital performance.

This research, therefore, aims at finding out how statistical computation can be used in analyzing as well as improving the performance management of a hospital in as much as quality and efficiency are concerned.

Literature Review

Key performance indicators (KPIs) for hospitals as stated in the research were as follows: The KPIs for the management of hospitals were the main focus of the research [8], the DEMATEL and Z-numbers big group evaluation approach. To set specific targets in cause-and-effect relationships, the technique improved the DEMATEL approach and used complicated interconnections among indicators. It was highlighted that this strategy proved effective in the case of a rehabilitation facility, key performance indicators of which were occurrences, accidents, nosocomial infections, technological pass rate, and length of care.

To address the aspect of unpredictability in hospital performance evaluation (HPE), the study [9] proposed a comprehensive multi-criteria group decision-making (GDM) model. It developed a framework of GDM by integrating fuzzy preference programming (FPP) and the best-worst method (BWM). Reliability calculations were not present in the model because the study merged the GDM method into one model. In the study that was conducted on five hospitals, the efficiency of the suggested framework was ascertained.

Based on the belief function theory (BFT), new improvements to the best-worst method (BWM) for measured uncertain hospital service quality were described in the study [10]. The procedure involved in implemented the study also came with a guideline to evaluate hospital service quality. To illustrated the effectiveness of the proposed concept and gave directions for the evaluation of the healthcare sector.

Research conducted in the study provided an approach for measuring the service quality of hospitals in the existing and increased competition in the healthcare industry [11]. To provide a systematic approach to decision, the model incorporated techniques. Based on the 32 quality of service criteria and two hospitals, private as well as public, the study aimed at proving the viability of the suggested strategy and at the same time, gauging the effectiveness of the proposed strategy.

A paradigm known as comprehensive multi-criteria decision-making (MCDM) was used in the research [12] to assess the supply chain efficiency of top healthcare companies. The results of three MCDM frameworks displayed consistency, and the results indicated that big-cap corporations do not always perform well. The study stressed the need to use financial measures to assess supply chain effectiveness.

Hospital service quality in recognized hospitals was studied in the article [13] about the components of Total Quality Management (TQM). The results of the study demonstrated that the quality of services provided by hospitals was favorably impacted by organizational culture, process management, customer focus, teamwork, and dedication from top management. Hospital administrators were able to improve their processes and add to the body of knowledge on TQM.

Pay-for-performance incentives were the primary objective of the study [14], which looked at how healthcare digitization affected the funding of smart hospital projects. Digital platforms increase the scalable value of networks by allowing exchanges between interacting agents. With the growing patient-centricity of digital logistics in medical public-private partnerships (PPPs), that was especially pertinent. This research study analyzed the expenditures and benefits of digital health, found bottlenecks in the supply chain, and made recommendations for networking platforms.

Data envelopment analysis (DEA) was used in the study [15] to examine the effectiveness of the healthcare systems. Senegal was found to be the least efficient system, with 21 (58.33%) of the systems being effective. According to the study, achieved the same health results required the efficient use of both public and private health resources. Effectiveness and efficiency within healthcare systems might be guaranteed by comparing their performance through worldwide comparison.

Methodology

Data Collection

The dataset followed specific criteria set forth by the regulatory body overseeing craniotomy procedures. Missing data underwent meticulous handling through established risk models sanctioned. Statistical analyses encompassed isolated craniotomy procedures across a network involving 180 Hospitals. From 2019 to 2023, data derived from 48,521 procedures formed the basis for model development. Hospital rankings in 2023 stemmed from outcomes derived from 18,654 craniotomy surgeries.

Measurements

A craniotomy is a surgical procedure involving the deliberate opening of the skull to access the brain. It is primarily employed for the surgical removal of brain tumors, treatment of traumatic brain injuries causing intracranial hematomas, and alleviation of intracranial pressure due to cerebral edema or other pathologies. Outcome Measures: The success and safety of craniotomy are evaluated through two primary outcome measures: operative Death rate and severe complications or death. Operative Death rate assesses the immediate survival rate post-surgery. Severe complications or death, a composite measure, encompasses permanent stroke (cerebrovascular accident), renal failure, and the necessity for reoperation due to various complications.

Statistical model approaches

Risk Assessment

Risk assessment for craniotomy procedures involves employing three main types of risk-adjustment models: Full fixed effect models that let in characteristics of every hospital, simple logistic regression models that are not hospital effects and random effect models that allow for variability across the hospitals. These models are applied in two stages: first, to calculate coefficients for the factors such as age, other diseases and type of surgery via patient level data, second, to evaluate hospital specific impact for specific years with the help of these coefficients and in order to compose the rates for such indicators as Death rate and severe Complication or death. When it comes to evaluating these models, it is crucial to evaluate stability across different approaches and to guarantee that they are less sensitive to variations in patient and procedural characteristics when it comes to predicting the results of surgical procedures.

Craniotomy Rate Estimation Using Direct and Indirect Standardization

Surgical severe complications or death rates after craniotomy were determined utilizing direct and indirect standardized analyses and adjusted for hospital-related characteristics using risk-adjustment models. Direct method of standardization included assuming a standard case mix for all the admissions across the hospitals using a combined patient population across the dataset. Two approaches were employed: Fixed-effect estimates were obtained using two models: DS_fixed, where the fixed effects were hospital-specific, and DS_random, where the random effects were also estimated at the hospital level, known as contraction estimates. Calculating Predictive to Expecting (P/E) or Observed-to-expecting (O/E) ratios was made possible via the use of three different indirect standardization techniques. All of the hospital's adjusted patient risks added along with the following formula was used to calculate each hospital's expected number of events (E).

Whether the standard logistic model without hospital effects ("IS_logit"), the median hospital impact from fixed effect models ("IS_fixed"), or the random effect models' ("IS_random") standard hospital effect. The identified patients undergoing outcomes (operative death rate, severe complications, or death) at each institution were used to calculate the total observed event (O) in the O/E ratio.Confidence intervals (CI) for O/E ratios were constructed using Clopper-Pearson exact binomial methods, ensuring robust statistical estimation. The 95% confidence intervals (CIs) for the P/E ratio were constructed using bootstrap techniques, and Adding hospital-specific random effects to random effect models allowed for the computation of the projected number of occurrences (P) in P/E ratios. The indirect standardization rates with every hospital were then obtained by the entire result value multiplied by hospital-specific O/E ratios ("IS_fixed" or "IS_logit") or P/E ratios ("IS_random").

Exponential Smoothing approach

Exponential smoothing methods were employed to estimate rates of surgical outcomes following craniotomy procedures. This method involves iteratively updating forecasts based on weighted averages of past observations, with recent data receiving higher weights. Hospital performance was assessed based on smoothed rates, considering statistical criteria for distinguishing hospital-specific outcomes from the average rate.

Observations arranged chronologically are called time series. One of the most often used methods for creating a smoothed time series is exponential smoothing. Weights are assigned via exponential smoothing, which decreases them exponentially with increasing observation age. The following formula explains how exponential smoothing works.

$$E_s = E_{(s-1)} + \alpha \left(B_{(s-1)} - E_{(s-1)}\right) \tag{1}$$

Comparison of modeling approaches

The different statistical techniques used in this study include the following in analyzing and comparing the results from the craniotomy procedures. Firstly, we analyzed how hospital-specific outcome rates are distributed and if they are correlated, based on the different statistical methods used. These competencies involved assessing how each paradigm addressed the differences in outcome rates across hospitals. Secondly, we compared the hospital rankings estimated using the approach by calculating the standardized rates. This helped in the generation of results that pointed out any differences or similarities in the rank of hospitals depending on their efficiency in handling surgical risks. Finally, we examine performance outliers by 97% confidence intervals. Hospitals were categorized as ‘better’ if their P/E ratio or O/E ratio had a confidence interval of 97% < 1, which means that the outcome rate of the hospitals was lesser than the predictabledespicable rate. On the other hand, if the calculated O/E or P/E has a 97% confidence interval greater than 1, it is defined as a worse hospital.

When conducting the two-tailed significance tests, statistical significance at $p < 0.05$ was maintained for all the tests done to compare across the hospital terciles, the ANOVA was used. The strength and direction of the correlation between rates were quantified using the Pearson correlation coefficient (r). Statistical analyses were performed using SPSS Statistics, Version 27, and R version 4.1.0.

Result

Variation in Hospital Results

The despicable observed rate of death rate among the 180 participating hospitals was 2% (range: 0%–10%; standard deviation (std): 2%), whereas the mean observed rate of severe complications or death was 11% (std: 5%; range: 3%–35%). The effectiveness of the method was assessed for three different procedure volume tiers: compact (less than 98 cases annually), moderate (98–185), and extended (more than 185). Smaller hospitals exhibited greater variation in outcomes (operative Death rate range: 0%-15.0%; Severe complications or death range: 3%-35%) compared to larger hospitals (operative Death rate range: 0%-4%; Severe complications or death range:7%-16%), as illustrated in Supplemental Figure 1. No significant differences were found in hospital operative Death rate or Severe complications or death rates diagonally hospital capacity terciles (Death rate ANOVA p-value = 0.85; p-value for Severe complications or death = 0.29).

Hospital outcome variance was decreased by methods utilizing contraction estimations

The fluctuation of standardized rates was decreased by the approaches that employed contraction estimates (IS_random, DS_random, and Exponential smoothing) (see Figure 1a). When employing non-contraction techniques, the boxplot shows that the surgical rate of death was distributed according to hospital terciles standards for each hospital. For instance, in the compact hospital terciles, the rates produced by IS_logit ranged from 0% to 7%, whereas the rates produced by IS_fixed and DS_fixed ranged from 0% to 7% and 0% to 6.5%. While contraction approaches exhibited less volatility in the outcomes than non-contraction methods, still, for every hospital terciles, they exhibited a similar range of standardized rates. For the following techniques, the distribution of contraction approaches in the compact hospital terciles was comparable: Exponential smoothing (2%-3%),DS_random (2%-2.5%), and IS_random (standardized rates min-max: 2%-2.5%) (Figure 1a). When compared to non-contraction procedures, contraction methods also reduced hospital variance in significant morbidity or death (see Figure1b).The terms "DS_fixed" and "DS_random" refer to direct standards using models of fixed effects, "IS_logit" and "IS_fixed" to logistic models of regression for indirect standardization, and "exponential smoothing" to the exponential smoothing model. a) death rate; b) Severe complications or death.

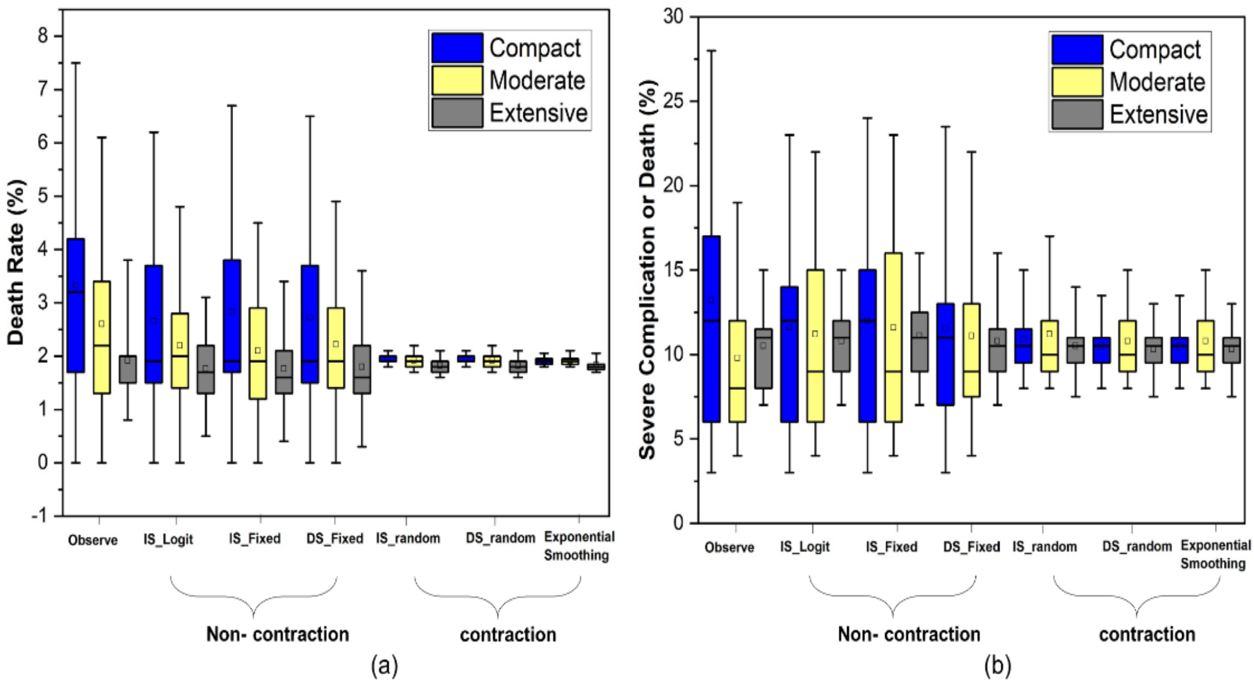

Figure 1: Standardized rate distributions across statistical techniques

Hospital standardized rates were pushed toward the average by the contraction techniques, especially for smaller hospitals. For instance, the IS_fixed approach (a non-contraction method) yielded standardized death rates of more than 6% in 7compact hospitals. These hospitals' standardized rates were more in line with the 2% average rate following contraction using the IS_random approach (see Figure 2a). The standardized rates obtained with the IS_random approach for hospitals with a 0Death rate ranged from 2% to 2.5%. Direct standardization techniques produced comparable results (DS_random vs. DS_ fixed, Pearson correlation r = 0.92; Figure 2b). Severe complications or death, which had greater event rates, also showed a comparable contraction impact (see Figures 2c and 2d). The IS_random standardized rate following contraction was 17% with two small hospitals having IS_fixed standardized rates of 26%. For DS_random vs. DS_fixed and IS_random vs. IS_fixed, the standardized rates showed a good correlation (r = 0.96 and 0.97, respectively). For every technique, the standardized rates are displayed in scatter plots. A hospital is represented by each bubble, and the size of the bubble represents the facility's proportional case volume. a) The indirect standardized rates for mortality rate are correlated between the IS_random (contraction technique) and Indir_fixed (non-contraction approach). P <.0001, r = 0.915. b) The relationship between the death rate for direct standardized rates derived using the contraction technique DS_random and the non-contraction approach DS_fixed is presented. r = 0.916, P <.0001. c) IS_random vs. IS_fixed indirect standardized rates correlation for significant severe complication or death when the outcome is displayed. r = 0.972 (p < .0001). d) The direct standardized rates from DS_random vs. DS_fixed are correlated with significant severe complication or death as the outcome. r = 0.956 (p < .0001).

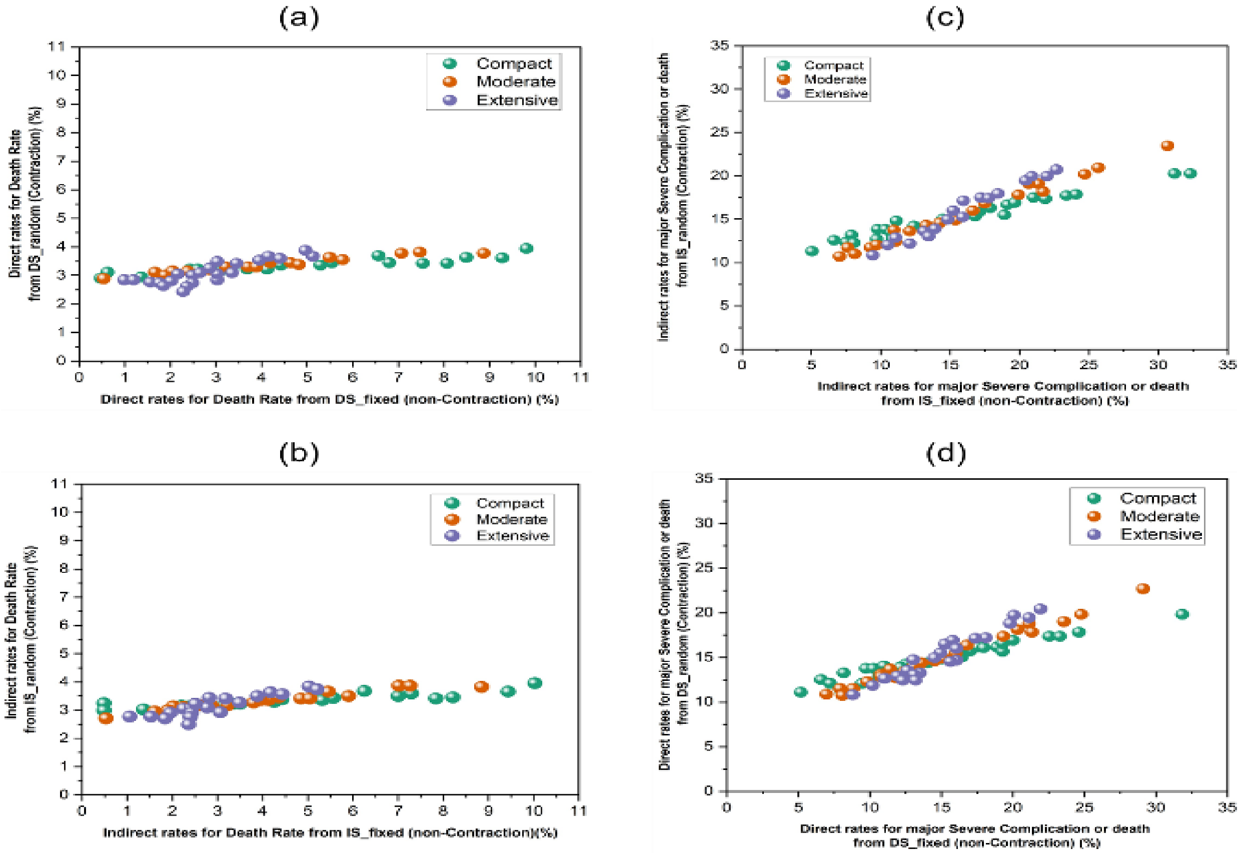

Figure 2: Reducing Hospital Variability through Contraction Methods

Methods with contraction change hospital rankings

As various techniques altered the standardized rates, the absolute hospital rankings also shifted (see Figure 2). Hospitals' absolute rankings were used to divide them into quintiles to measure the shift in rankings. If the DS_random approach was used instead of the DS_fixed technique for the Death rate quintiles rankings, hospitals in every quintile rank saw changes in their quintile ranks that ranged from 17% to 39% (Table 1b). For instance, small hospitals were reclassified into the second and third quintile rankings with the DS_random techniques, respectively, after being in the first death rate quintile rank under the DS_fixed method for 22% and 6% of the hospitals. Table 2 (b) shows that 6% to 28% of hospitals in each quintile had their rankings altered when contraction techniques (DS_random) were applied to severe complications or death quintile rankings based on non-contraction methods (DS_fixed). Quintile differences between the different methods.

Table 1: (a) Hospital death rate quintiles ranking changes

Quintiles with contraction based on the DS_random technique	**Quintiles derived using the DS_fixed technique, no. (column %), without contraction**				
	1 “Micro”	2 “Small”	3 “Medium”	4 “Big”	5 “Huge”
1 “Micro”	26 (72%)	10 (28%)	-	-	-
2 “Small”	8 (22%)	22 (61%)	6 (17%)	-	-
3 “Medium”	2 (6%)	4 (11%)	26 (72%)	4 (11%)	-
4 “Big”	-	-	4 (11%)	26 (72%)	6 (17%)
5 “Huge”	-	-	-	6 (17%)	30 (83%)

Table 1: (b) Changes in Hospital Death Rate Quintiles Ranking

Hospitals with varying ranks in number	10 (28%)	7 (39%)	5 (28%)	5 (28%)	3 (17%)
Compact	8	4	0	4	2
Moderate	2	2	0	0	4
Extensive	0	8	10	6	0

Table 2: (a)Hospital Severe Complications or death quintiles ranking changes

Quintiles with contraction based on the DS_random technique	**Quintiles derived using the DS_fixed technique, no. (column %), without contraction**				
	1 “Micro”	2 “Small”	3 “Medium”	4 “Big”	5 “Huge”
1 “Micro”	30 (83%)	6 (17%)	-	-	-
2 “Small”	6 (17%)	26 (72%)	4 (11%)	-	-
3 “Medium”	-	4 (11%)	30 (83%)	2 (6%)	-
4 “Big”	-	-	2 (6%)	32 (89%)	2 (6%)
5 “Huge”	-	-	-	2 (6%)	34 (94%)

Table 2: (b)Changes in the Quintiles Ranking for Severe Complication or Death in Hospitals

Hospitals with different ranks in number	6 (17%)	10 (28%)	6 (17%)	4 (11%)	2 (6%)
Compact	6	4	0	2	2
Moderate	0	2	2	0	0
Extensive	0	4	4	2	0

When the contraction techniques were used, compact hospitals shifted toward the middle of the hospital rating, leaving fewer compact hospitals in the top and bottom 10% of the ranking. For instance, 10 compact and 8 moderate hospitals performed in the top 10% of hospitals using approaches without contraction (IS_logit, DS_fixed, and DS_random), whereas 12 compact and 6 moderate hospitals performed in the poorest 15% of hospitals. In contraction methods (IS_random, DS_random, exponential smoothing), 0 compact, 16 extensive, or 2 moderate-sized hospitals performed in the highest 15%, while 8 compact, 6 moderate, and 4 extensive hospitals ranked in the poorest 15% for the death rate.

Various performance outliers were detected using methods.

To look for performance outliers in each technique, we compared the predicted or actual rates to the predictable rates (moderate hospital impact) and determined whether various approaches produced separate performance outliers. Concerning death rates, the 2 compact hospitals and 6 moderate-sized hospitals found using the IS_logit and IS_fixed (O/E) methods had significantly higher observed rates than anticipated (poorer hospitals), while the 10 extensive hospitals found using the IS_random (P/E) method had significantly poorer predicted rates than probable (superior hospitals) (Figure 3). All 3 approaches (IS_logit, IS_fixed, and IS_random) identified compact and extensive hospitals as performance outliers for the most frequent severe complications or death outcomes; however, the methodologies yielded different hospital outliers (Figure 3).

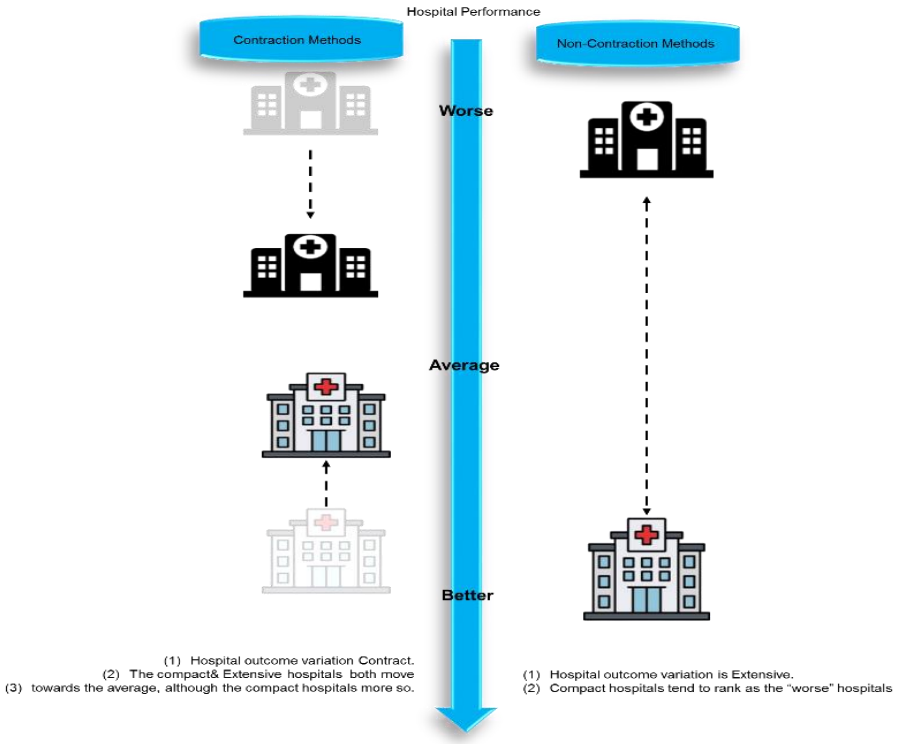

Figure 3: Methods and their influence on hospital rankings

Conclusion

In conclusion, this study underscores the critical role of statistical methodologies in assessing and improving hospital performance during quality improvement initiatives. By evaluating six established statistical approaches using a comprehensive dataset spanning 48,521 patients undergoing craniotomy surgery across 180 hospitals from 2019 to 2023, significant insights have been gathered. Non-contraction methods such as indirect standardization with and without fixed effects, alongside direct standardization with fixed effects, provided a baseline for comparison against contraction methods including indirect and direct standardization with random effects, and Exponential Smoothing. The findings highlight that contraction methods effectively reduced inter-hospital variation in operative death rates and severe complications or death, thereby aligning hospital performance rates closer to the group despicable. Notably, direct regulation incorporating hospital random effects led to substantial changes in mortality quintile rankings compared to fixed effects, demonstrating the sensitivity of rankings to methodological choice. Moreover, the absence of performance outliers among compact and moderate hospitals for death rate with indirect standardization and random effects contrasts with the identification of outliers using logistic and fixed effect methods. Overall, the study underscores the importance of methodological rigor in benchmarking hospital performance. These insights are pivotal for healthcare stakeholders aiming to enhance quality improvement strategies and effectively benchmark hospital performance across diverse healthcare settings.

Limitations & Future Scope

The study is subject to specific limitations, such as possible biases in data resulting from dependence on registry data, variations in risk adjustment methods, and the applicability of results restricted to craniotomy surgery and certain statistical techniques. Future research could explore broader applications across diverse surgical procedures, refine statistical models to enhance accuracy, and integrate real-time data analytics for continuous quality improvement in healthcare settings.

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