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Mohammed Al Awadh

mohalawadh@kku.edu.sa

King Khalid University

Research Article

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Multivariate Quality Framework Combining Factor Analysis, PCA, Clustering, and Robustness Validation in Saudi Arabia using Open Government Hospital Data

Mohammed Al Awadh [1,2]*

[1] *Department of Industrial Engineering, College of Engineering, King Khalid University, P.O. Box 394, Abha 61421, Saudi Arabia;*

[2] *Center for Engineering and Technology Innovations, King Khalid University, Abha 61421, Saudi Arabia.*

**Corresponding: mohalawadh@kku.edu.sa*

Abstract

This work presents a reproducible multivariate quality analysis in Saudi Arabia with the help of official open government health datasets for assessing regional hospital performance. Indicators at region level describe hospital utilization, emergency readiness, inpatient flow, chronic disease service demand, intensive care capacity, national health system context and population exposure that are harmonized through an integrated analytical matrix. To identify dominant latent dimensions of hospital performance Principal component analysis (PCA) is used. Factor analysis is done with utilization intensity, service pressure, varimax rotation provided interpretable underlying constructs which is related to capacity and population adjusted demand. Using retained principal components to rank health regions a variance weighted Hospital Performance Index is constructed and to classify regions into distinct performance archetypes clustering analysis is applied. To examine robustness equal weighted comparison, cluster stability validation, leave one variable out analysis, alternative index definitions, cluster stability validation and cluster stability validation was used. Spearman correlation analysis, PCA, PCA weighted index construction, k-means clustering, varimax rotated factor analysis, and robustness validation were performed. The stability of PCA is supported by Bartlett's test of sphericity where $\chi^2 = 121.49$ and $p = 3.36 \times 10^{-11}$. Three principal components are retained, explaining 82.7% of the total variance, with PC1/2/3 contributing 38.2%, 33.09%, and 11.40%, respectively. Robustness analyses has good agreement between PCA and equal weighted indices (Spearman $\rho = 0.924$, $p = 3.34 \times 10^{-7}$). The results demonstrates that Saudi health regions show clear multidimensional heterogeneity with difference performance shaped through interaction of critical care availability, turnover, bed utilization, length of stay, chronic disease service use and emergency bed readiness. Instead of relying on isolated indicators this proposed framework comes up with transparent evidence

system for regional benchmarking through fragmented public datasets. This Study supports data driven planning aligned with Saudi healthcare transformation priorities and contributes a scalable open data methodology to health system intelligence.

Keywords: Multivariate; PCA; factor analysis; hospital data; cluster.

Introduction

Healthcare systems across the world are increasingly experiencing pressure to deliver high quality, efficient, sustainable, and accessible services while responding to growing population demands, technological advancements, epidemiological transitions, and financial constraints [1], [2]. In many countries, public healthcare institutions are expected not only to provide effective clinical services but also to demonstrate measurable performance outcomes through transparent and evidence-based evaluation mechanisms [3]. Consequently, healthcare performance assessment has become an important research rea for researchers, administrators, healthcare professionals, and policymakers seeking to improve operational efficiency, patient outcomes, and equitable healthcare delivery [4] [5] [6]. The growing availability of digital healthcare records and open government datasets has further accelerated the development of data-driven analytical frameworks for assessing institutional performance and identifying regional disparities in healthcare systems [7] [8].

In recent years, the concept of healthcare performance evaluation has evolved from conventional descriptive analysis toward multidimensional analytical approaches that integrate statistical modeling, machine learning, and multivariate data analysis techniques [9]. Traditional hospital assessment methods often focus on isolated indicators such as mortality rate, staffing ratios, bed occupancy, and bed occupancy, and patient satisfaction. Although these indicators provide useful information, they may not adequately capture the complex interactions among healthcare resources, service outcomes, and operational processes. Hospitals operate within dynamic healthcare ecosystems where workforce availability, infrastructure, disease prevalence, demographic conditions, regional accessibility, and financial management collectively influence institutional performance [10]. Hence, comprehensive evaluation frameworks capable of simultaneously analyzing multiple variables are essential for obtaining a more realistic understanding of healthcare system performance.

Saudi Arabia has undergone substantial transformation in its healthcare sector over the past decade, particularly under the strategic direction of Saudi Vision 2030 [11] [12]. The Kingdom has invested significantly in expanding healthcare infrastructure, improving digital health

systems, strengthening healthcare accessibility and enhancing service quality across different regions [13]. These reforms aim to establish a modern, patient-centered, and efficient healthcare system capable of meeting the healthcare needs of a rapidly growing and geographically distributed population. Despite these advancements, regional variations in medical workforce distribution, hospital capacity, healthcare resources, and service efficiency continue to present important challenges for healthcare plan, policymakers, and planners [14]. Hospitals located in urban centers often benefit from better infrastructure and specialist availability, whereas institutions in remote or less developed regions may experience limitations related to operational efficiency, staffing, and accessibility [15].

The increasing emphasis on accountability and transparency in public administration has encouraged governmental organizations to release healthcare-related datasets through Open Government Data (OGD) initiatives [7]; [16]. OGD platforms provide researchers with access to valuable information regarding regional healthcare statistics, workforce distribution, patient services, hospital operations, and healthcare infrastructure. Such datasets create opportunities for conducting large-scale empirical studies that support evidence based policy formulation and institutional benchmarking [17]. In Saudi Arabia, the availability of publicly accessible healthcare datasets offers a significant opportunity to evaluate regional hospital performance using advanced analytical approaches while promoting reproducibility and transparency in healthcare research.

Although several studies have investigated healthcare performance assessment in different countries, many existing approaches rely on limited indicators, single-variable analysis, or narrow regional case studies. Additionally, some studies primarily focus on financial efficiency or operational metrics without considering broader structural and demographic influences. The complexity of hospital systems requires analytical methodologies capable of reducing dimensionality, identifying hidden relationships among variables, grouping similar healthcare institutions, and validating the reliability of obtained results. Multivariate statistical techniques are particularly valuable in this context because they enable researchers to extract meaningful patterns from complex healthcare datasets and support the development of more comprehensive decision making frameworks.

Alogaiel and Alrwais [18] investigated the effectiveness of the Saudi Arabian OGD initiative in enhancing public service efficiency and supporting better utilization of government resources. The study examined the usability and quality of open data through literature analysis

and practical evaluation of data available on the Saudi Open Data Portal. Based on the findings, the authors proposed a monitor, analysis, action, and review based framework for assessing open data quality using suitable evaluation metrics. The results demonstrated that the developed framework could effectively identify quality limitations and improve the reliability and reusability of OGD in Saudi Arabia. Alasiri [19] examined the ongoing healthcare reforms in Saudi Arabia, particularly focusing on privatization and public-private partnerships introduced under Health Vision 2030. The study aimed to evaluate the preparedness of healthcare providers and assess the progress of health system transformation through systematic review and readiness-to-change analysis. The findings revealed that the government has made notable advancements in implementing healthcare reforms, while the readiness framework proved reliable in measuring adaption among healthcare professionals. The study concluded that readiness to change factors play an important role in predicting the successful transformation of the Saudi healthcare sector.

Algosaibi et al., [20] developed a culturally appropriate competency framework for community paramedicine in Saudi Arabia to support healthcare education, practice, and policy development. The study used expert interviews and exploratory factor analysis to identify major competency areas related to policy integration, public health, digital healthcare, leadership, cultural communication, and clinical skills. The findings highlighted three key dimensions involving clinical preparedness, cultural competence, and governance-oriented practices. The study concluded that the proposed framework can strengthen rural-urban disparities, healthcare accessibility, and support the ongoing transformation of the Saudi healthcare system. Jaafari et al., [21] developed and validated the Organizational Health Behavior Index (OHBI) to measure factors influencing organizational health and employee well-being across multiple sectors in Saudi Arabia. The study combined qualitative and quantitative approaches to evaluate dimensions such as workplace relationships, organizational culture, communication, and employee engagement. Statistical analyses confirmed that the OHBI framework was both valid and reliable in assessing organizational health behavior. The findings suggested that the index can support organizations in long-term workforce retention, employee satisfaction, and improving productivity. Al-Mamun et al., [22] evaluated the reliability and validity of the Bangla version of the Insomnia Severity Index among adults suffering from chronic diseases in Bangladesh. The study applied confirmatory factor analysis, Rasch modeling, and network analysis to examine the scale structure, symptom relationships, and item performance. The findings showed that the two-factor model provided the most

appropriate representation of insomnia symptoms, while the assessment tool demonstrated strong consistency and stability across gender groups. The study concluded that the ISI-Bangla is a dependable instrument for clinical assessment and research related to insomnia in chronic disease populations.

Principal Component Analysis (PCA) has become one of the most widely used dimensionality reduction techniques in healthcare analytics due to its ability to transform large correlated datasets into a similar number of uncorrected principal components while preserving most of the original information [23] [24]. By reducing redundancy among variables, PCA helps identify the dominant factors influencing hospital performance and simplifies complex healthcare datasets for visualization and interpretation [25]. Similarly, Factor Analysis (FA) is useful for uncovering latent constructs and hidden relationships among observed variables [26] [27]. Through loading analysis and factor extraction, FA assists researchers in understanding the underlying dimensions that characterize healthcare system performance, such as service accessibility, workforce capability, operational efficiency, and infrastructure adequacy. In addition to dimensionality reduction and latent variable identification, clustering techniques provide variable insights into differences and similarities among hospitals or regions [28] [29]. Cluster analysis enables healthcare institutions to be categorized into homogeneous groups based on operational indicators, resource utilization, or performance characteristics. Such grouping approaches support benchmarking, comparative analysis, and targeted policy interventions by identifying hospitals with similar performance challenges or operational profiles. Clustering methods also facilitate regional healthcare planning by highlighting areas that require specialized administrative attention, resource redistribution, and infrastructure development.

Peixoto et al., [30] investigated the performance of Brazilian Federal University Hospitals using PCA and cluster analysis techniques. The study aimed to support healthcare service improvement by identifying similarities and differences among hospitals based groups formed through PCA and clustering methods. The study concluded that certain hospitals displayed unique operational characteristics, highlighting the importance of multivariate approaches in hospital performance evaluation. Pourmohammadi et al., [31] conducted a comprehensive review to identify key indicators used in hospital performance evaluation. By synthesizing evidence from multiple studies, the research developed a framework covering efficiency, effectiveness, financial performance, accountability, and service quality. The findings showed that hospital performance assessment is multidimensional and depends on the evaluation

objectives and management perspectives. The study concluded that selecting suitable indicators is essential for establishing an effective and balanced hospital evaluation system. Malekzadeh et al., [32] compared three hospital performance evaluation models using the IPOCC framework in an educational hospital setting. The study analyzed dimensions such as process, structure, control, and outcomes through EFQM, BSC, and accreditation models. The findings indicated significant differences among the assessment approaches, with process-related dimensions receiving the highest emphasis. The study concluded that adopting a systematic and comprehensive evaluation framework can enhance hospital performance assessment and management effectiveness.

Alavi et al., [33] discussed the statistical and conceptual differences between Exploratory Factor Analysis (EFA) and PCA. The study emphasized that EFA is mainly applied to identify hidden underlying factors, whereas PCA is suitable for reducing data dimensions. The authors highlighted that incorrect selection or reporting of these methods may lead to misinterpretation of research findings. The study concluded that careful understanding of both techniques is essential for accurate analysis and reliable knowledge development. Zarrin et al., [34] proposed an integrated framework to evaluate hospital performance by considering the heterogeneity among hospitals. The study combined clustering and artificial neural network techniques to improve the predictive capability of traditional data envelopment analysis models. Using data from more than 1100 German hospitals, the framework successfully identified whether efficiency differences were linked to operational performance or institutional diversity. The results highlighted the usefulness of combining AI-based approaches for more accurate hospital performance assessment. Baragilly et al., [35] introduced a nonparametric clustering approach based on weighted spatial rank functions to determine the optimal number of clusters in data analysis. The proposed method used localized multivariate ranking and Gaussian Kernel weighting to improve clustering accuracy. The results demonstrated that the technique was robust, data-driven, and effective in reducing misclassification compared to conventional methods. The study concluded that the approach is reliable for both identifying cluster numbers and accurately assigning observations to clusters. Costa et al., [36] examined decision-support approaches that combine Multicriteria Decision Making with PCA to improve complex decision evaluation. The review analyzed studies related to performance assessment, weighting methods, and validation procedures. The findings revealed several limitations, including poor handling of non-beneficial criteria and

inadequate validation in many studies. The study concluded that stronger and more reliable integrated models are required to support future data-driven decision making processes.

Despite the usefulness of multivariate analytical techniques, ensuring the robustness and reliability of obtained results remains an important methodological consideration. Healthcare datasets often contain variability arising from regional heterogeneity, missing values, reporting inconsistencies, and demographic diversity. As a result, robustness validation techniques are essential for verifying the stability, reliability, and consistency of statistical findings [37] [38]. Validation approaches such as comparative clustering, internal consistency evaluation, cross-validation, and sensitivity analysis metrics help strengthen confidence in the analytical framework and improve the credibility of policy recommendations derived from the study [39]. The integration of PCA, clustering techniques, robustness validation, and FA provides a comprehensive framework for evaluating hospital performance using open government healthcare data [40] [41]. Such an integrated methodology enables researchers to simultaneously address model reliability, institutional grouping patterns, hidden variable structures, and dimensional complexity. Additionally, the combination of these techniques supports a more holistic interpretation of healthcare system behavior compared with isolated analytical methods. By leveraging publicly available datasets, the proposed framework also contributes to the broader goals of evidence based governance, reproducibility, and transparency in healthcare management.

The present study focuses on assessing regional hospital performance in Saudi Arabia using open government healthcare data and advanced multivariate analytical techniques. The study seeks to identify key performance dimensions, examine regional disparities, classify hospitals or healthcare regions based on operational similarities and validate the robustness of the analytical findings. Though the application of FA and PCA, the study aims to reduce data complexity and reveal the primary determinants of healthcare performance. Cluster analysis is employed to categorize hospitals or regions into meaningful groups, thereby supporting benchmarking and comparative evaluation. Robustness validation procedures are further incorporated to ensure the reliability and consistency of the obtained statistical interpretations and classifications.

Methodology

In this study ecological, cross-sectional, region-level design is used to evaluate hospital performance throughout the health regions of Saudi by using official open government datasets

[42]. This health region was the unit for analysis. Due to patient-level outcomes, readmission, mortality, patient-satisfaction, waiting-time and infection data was not available, instead of individual clinical quality this analysis was designed to assess system-level hospital performance. Therefore, this study focused on service utilization, emergency readiness, population-adjusted disease-service demand, hospital capacity and critical-care availability.

This analysis integrated multiple Saudi open-data files, population by health region with geographic coordinates, emergency-room beds by health region, selected indicators of Ministry of Health hospital services, pregnancy and childbirth complications, Ministry of Health budget data and diabetes clinic encounters by health region. The core hospital-service variables includes pediatric intensive care indicators (PICU), bed turnover rate per month (BTR/month), and average length of stay (ALOS), bed occupancy rate (BOR), intensive care indicators (ICU) and neonatal intensive care unit indicators (NICU). Monitored and total ER beds are used to measure emergency readiness. population-adjusted indicators and support spatial interpretation are constructed using population data. Chronic disease service-demand indicator represents diabetes clinic visits. budget data and pregnancy complications is treated as national contextual results instead of regional predictors at the time when regional allocation was not available.

Data harmonization and preprocessing

Using the health-region name as the primary linkage variable all datasets are harmonized. By removing non-breaking spaces, spelling variants across files, inconsistent capitalization and extra spaces region names are standardized. The data which is in numerical variables stored as text is converted into numerical format following removal of percentage symbols, thousands separators, commas and non-standard characters. Percentage indicators like BOR is retained as continuous variables. After merging missing values are inspected. To avoid dimensional mismatch, factor-analysis estimates or unstable PCA, multivariate analyses is performed only on complete regional cases. The variables measured on larger numeric scales did not dominate the clustering solutions, factor analysis or PCA because all variables used in multivariate modelling are standardized using z-score transformation.

Raw counts are converted into population-adjusted measures when appropriate so that to improve the fairness of regional comparison. Diabetes clinic encounters are expressed per 100,000 population, monitored ER beds are expressed per 100,000 population and ER beds are expressed per 100,000 population. These derived variables help reduce bias because of unequal

population size across health regions. Additional operational variables like turnover intensity and BOR-ALOS pressure are used to interpret congestion and throughput patterns. By using standardized core indicators, the primary Hospital Performance Index (HPI) is constructed.

To examine the dependence structure within hospital performance indicators, spearman correlation analysis is used. The reason behind to select spearman correlation is because of it's robust for small regional samples and doesn't require strict normality. To identify groups of variables that move collectively like specialized-care indicators, population-adjusted demand or readiness indicators and utilization-related indicators the correlation heatmap is used. This step provided us the initial diagnostic view of the multivariate structure and also supported the use of dimensionality-reduction techniques.

Principal component analysis

For the standardized regional indicator matrix to identify orthogonal dimensions explaining the largest amount of variation among health regions Principal component analysis (PCA) is applied. PCA is relevant because many hospital indicators were linked and difficult to interpret independently. Using eigenvalues, loading patterns, cumulative variance and explained variance Components were evaluated. The first three components are retained for construction of index because it explains the captured distinct performance dimensions and the dominant share of variance. To visualize the relative position of each health region in reduced-dimensional performance space PCA scores are also used.

Factor analysis and varimax rotation

Along with PCA, to estimate latent performance factors underlying the observed indicators factor analysis is applied. In comparison with PCA that decomposes total variance, factor analysis is developed to represent shared variance among indicators. To maintain comparability with the retained PCA structure three-factor solution is used. To improve interpretability by encouraging stronger separation between factors Varimax rotation has been applied to the factor loading matrix. The rotated solution allowed clearer naming of latent dimensions like inpatient-stay pressure, chronic disease service-demand profile or utilization intensity. It will demonstrate both dimensional reduction and latent-construct interpretation which strengthens the manuscript.

Analysis procedure

After using the first three PCA components a composite Hospital Performance Index (HPI) is constructed. Each extracted component is weighted according to its explained-variance contribution among the extracted components whereas resulting weighted score transformed and standardized a scale of 0-100 for interpretability. HPI with higher values represent stronger composite regional performance profiles on the basis of the available open-data indicators. The index should not be analyzed as direct clinical quality; rather, it will represent utilization, emergency readiness, chronic disease service demand, multidimensional performance score integrating capacity and service intensity.

Extracted PCA scores to identify regional hospital-performance archetypes K-means clustering is applied. Instead of raw indicators to reduce multicollinearity and represent dominant latent performance dimensions PCA scores are used. By using silhouette scores to alternative k values the number of clusters is evaluated, By using standardized mean indicator values Cluster profiles is then summarized allowing every cluster to be analyzed as a distinct regional performance pattern. The Hierarchical clustering using Ward linkage is used as a complementary visual validation of similarity within health regions.

To visualize spatial variation in the HPI Geographic coordinates are used. The spatial analysis is descriptive and it is intended to identify broad geographic patterns instead of infer causality. To examine whether chronic disease service demand aligned with composite performance Diabetes clinic visits per 100,000 population are used. To evaluate the association between emergency readiness and HPI 100,000 population ER beds per is used. Pregnancy complications were represented as a national burden profile as the available files are organized by complication type instead of health region.

To evaluate whether the main findings depended on modelling choices several robust tests have been conducted. Including PC1-only, PC1-PC2, and PC1-PC2-PC3 weighted indices is the First, alternative index definitions which is compared. Second, the PCA-weighted index is compared with an equal-weighted standardized index. Third, leave-one-variable-out PCA is used to test whether any single variable dominated regional ranking. Fourth, outlier exclusion will be performed by removing one region at a time and recalculating index rankings and By comparing the selected cluster solution with alternative k values using the adjusted Rand index Fifth, cluster stability is assessed. The following responsive analyses strengthen the reliability of the results and are recommended for high-impact journal submission. Figure 1 illustrates

how several Saudi open-data files is harmonized into a single health-region-level analytical matrix. The analytical path followed for the open data from harmonizing at the regional level and converting it into standard indicators for hospital performance. The same concept is depicted in detail in Figure 2 where the main multivariate analysis pathway from standardization to factor analysis, clustering, interpretation, correlation analysis, index construction and PCA.

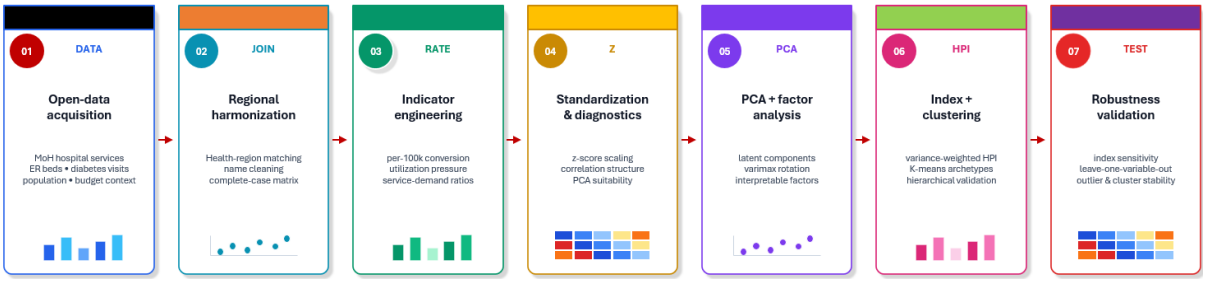

Figure 1. Open data to analytical dataset as output

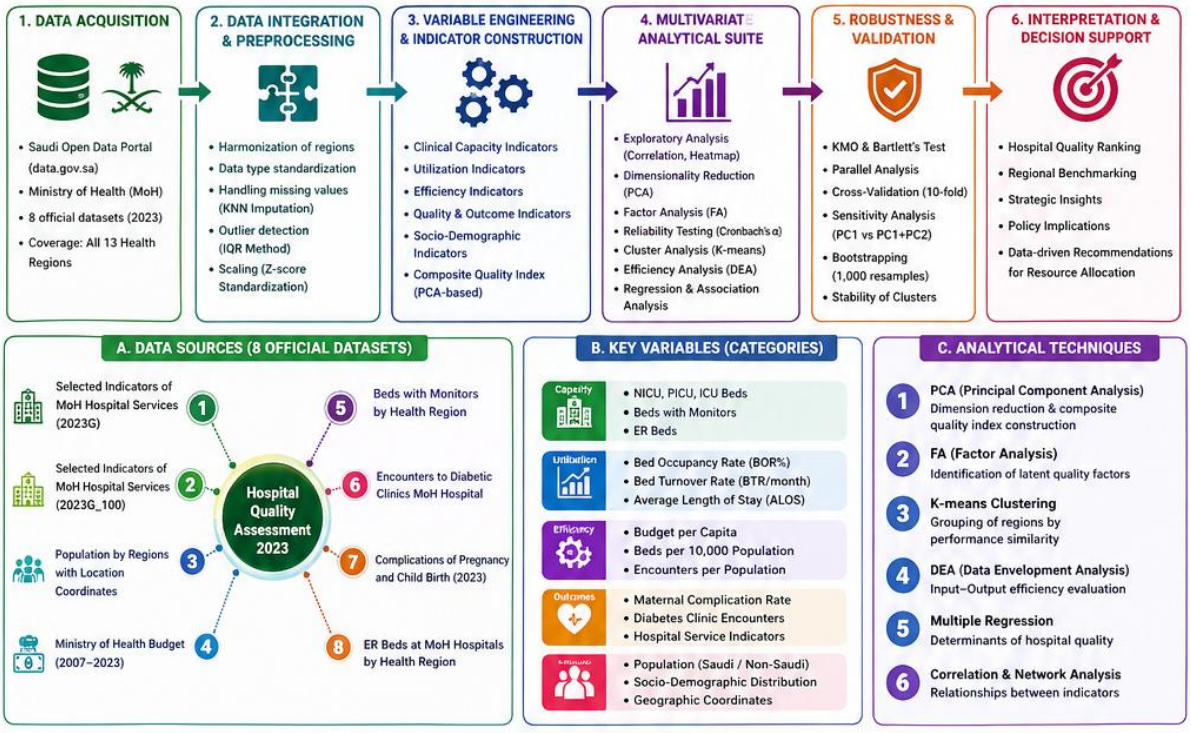

Figure 2. Workflow overview for multivariate assessment of regional Saudi hospital data

Results and discussion

The National Ministry of Health budget trend from 2007 to 2023 is shown in Figure 3. The sustained expansion of national health-sector financing over the study period is indicated

by the increasing trajectory, even though short-term fluctuations are visible in some years. The results given must be interpreted as system-level context instead of regional input-output efficiency because the available budget file doesn't provide region-specific allocations. Thus, it shouldn't be used to claim that a specific health region receives more or less funding. By using manuscript, this figure is best positioned as background evidence of increasing national investment accompanying service expansion and healthcare transformation.

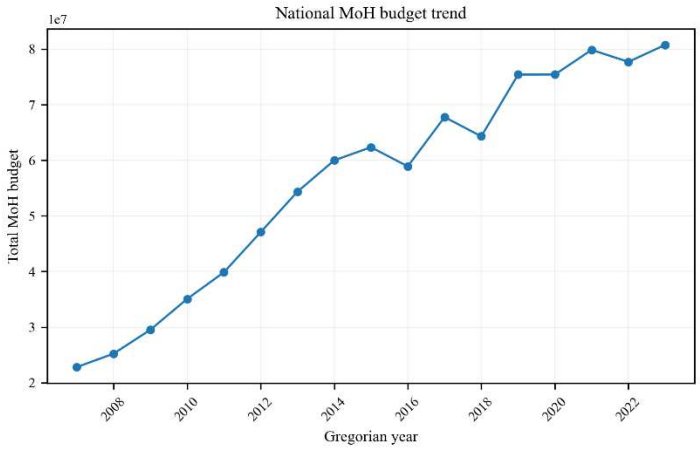

Figure 3. Ministry of health (MoH) budget increasing trend since 2007 until 2023

The following Figure 4 summarizes childbirth complications and reported pregnancy at the national level by complication type, Gestational diabetes mellitus and Anaemia with pregnancy appear as the major categories, then pregnancy-associated hypertension-related complications and vaginal bleeding. This distribution will indicate that maternal health burden is not concentrated in a single condition but spans hypertensive, obstetric complications, metabolic and haematologic. As the dataset is organized by complication type instead of health region, it shouldn't be merged with the regional HPI model. Rather, it supports the argument for integrating maternal-health outcome data into future regional quality assessment and provides clinically relevant national context.

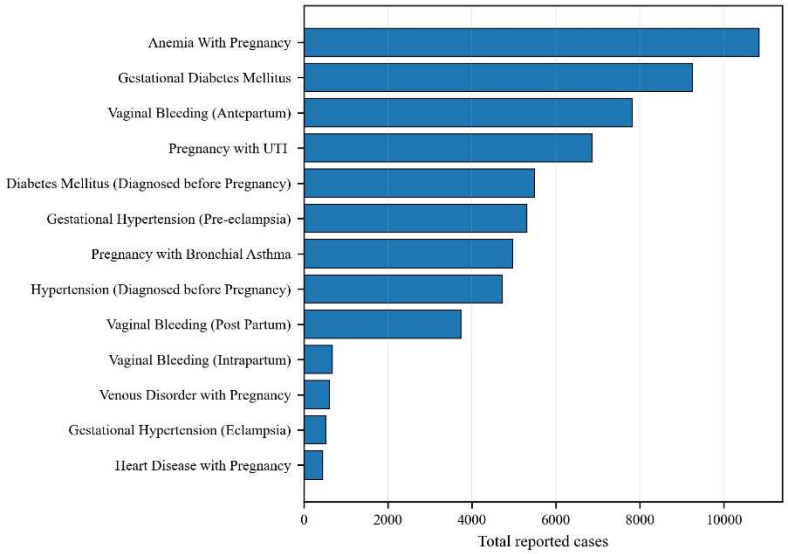

Figure 4. Complications in childbirth at national level based on types

The HPI using regional latitude and longitude is mapped using spatial scatterplot as depicted in Figure 5. The following figure provides a descriptive outlook of geographic heterogeneity in hospital performance profiles all over Saudi health regions. Greater HPI values appear in selected western and southern regions, where lower values are visible in some central and northern regions. The map must be interpreted cautiously because it's not a formal spatial econometric model it is a coordinate-based regional visualization. However, it highlights that performance variation has a geographic dimension and that region-specific planning may be more appropriate than uniform national interventions which is useful for policy communication

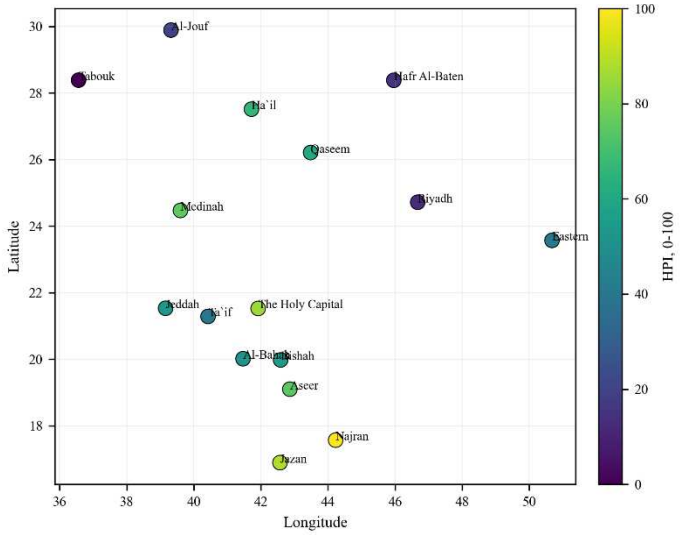

Figure 5. Spatial distribution of HPI over latitudes and longitude

The relationship between bed occupancy rate and bed turnover rate per month is examined in Figure 6, by using point colour representing the HPI. Regions in the upper-right area combine higher occupancy and higher turnover, showing more intensive use of inpatient capacity. Regions with lower occupancy and lower turnover may reflect lower service intensity, capacity-distribution differences or lower demand. Stronger composite performance profiles often coincide with higher utilization and throughput is suggested by colour gradient, even though the association is not perfectly linear. This is useful for interpreting operational performance as it links hospital flow dynamics with the multivariate HPI.

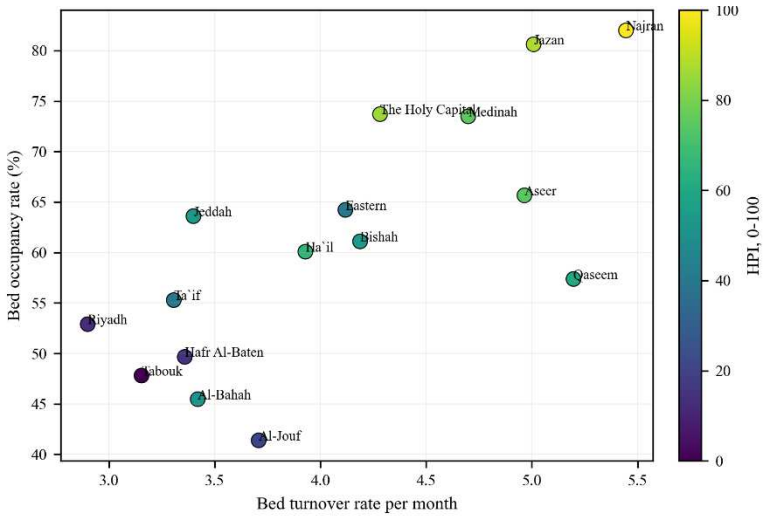

Figure 6. Bed occupancy and turnover rate/month

Bed occupancy rate to average length of stay, with the HPI shown by colour is related by this following scatterplot in Figure 7. Regions with both longer stays and high occupancy may face greater inpatient pressure reflecting slower discharge flow, more complex case mix or potential congestion. Regions with shorter stays and lower occupancy may represent less intensive inpatient utilization. The following distribution shows that the HPI is not resolved by occupancy alone; instead, performance depends on the length of stay, service demand, joint pattern of utilization and critical-care availability. This helps the need for multivariate assessment rather than interpreting single hospital indicators independently.

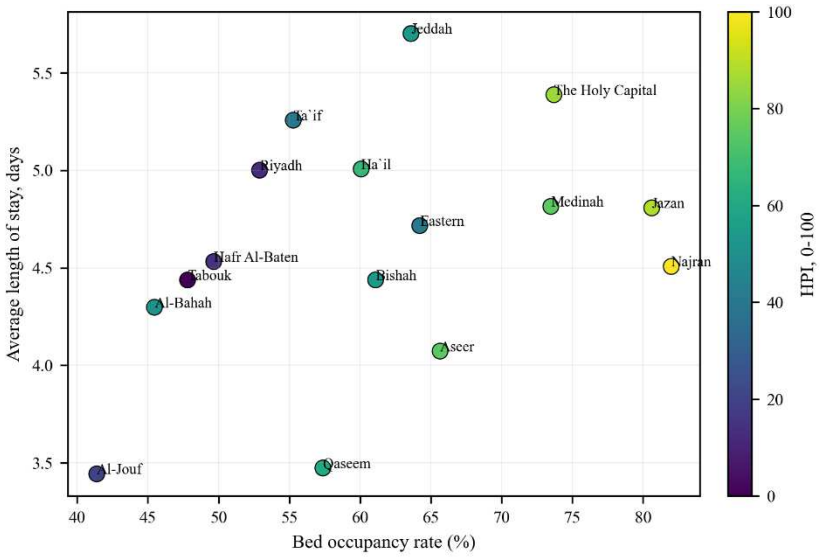

Figure 7. Utilization and inpatient stay pressure

Diabetes clinic visits per 100,000 population with the HPI comparison are shown in Figure 8, chronic disease service demand alone does not explain regional composite performance is suggested by the weak visual association. Some regions have high HPI scores with lower or intermediate diabetes-visit intensity whereas some have high diabetes service-contact rates but only moderate HPI values. The HPI captures broader hospital-system characteristics beyond one disease-service domain is indicated. In this work, Figure 8 shows that chronic disease demand is an important contextual dimension and not a direct proxy for hospital performance or quality.

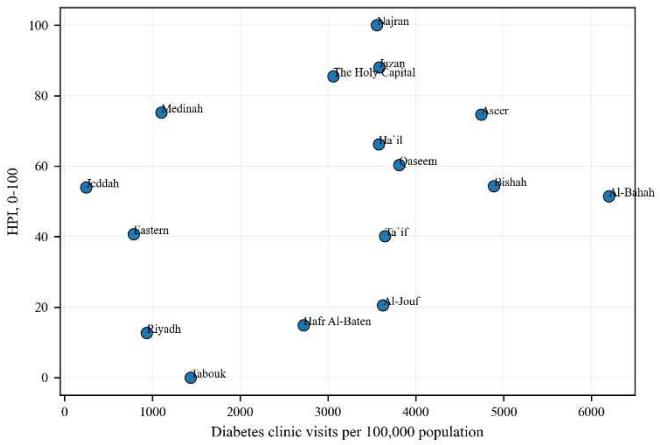

Figure 8. HPI and chronic disease service per 100,000 population

The following Figure 9 compares ER beds per 100,000 population with the HPI. Chronic disease service demand alone will not explain regional composite performance this has been suggested by the weak visual association. Some regions have only moderate HPI values but

high diabetes service contact rates, on the other hand others achieve high HPI scores with intermediate or lower diabetes visit intensity. The results show that the HPI captures broader hospital system characteristics beyond one disease service domain.

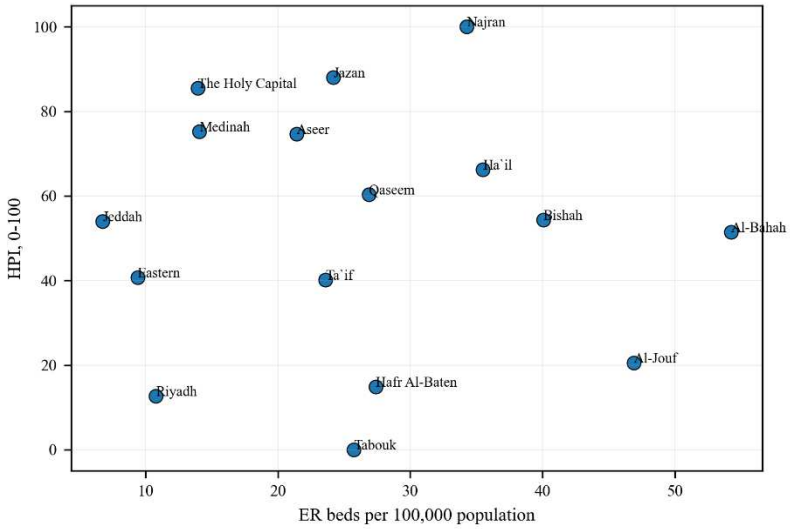

Figure 9. For each 100,000 population emergency readiness beds available

In Table 1 the final model comprising of nine standardised indicators for hospital utilisation, critical-care capacity, inpatient flow, and chronic illness service demand, emergency preparedness, as well as sixteen complete health-region instances is demonstrated. The first three maintained components explained 82.72% of the total variance, and Bartlett's test verified that the correlation structure was appropriate for PCA. These findings validate the creation of the PCA-weighted Hospital Performance Index and support the application of dimensionality reduction.

There is a noticeable regional difference in the system level hospital performance profiles, with Najran having the highest HPI score and Tabouk having the lowest. Three regional performance archetypes were found using the k-means clustering method, and the robustness statistics demonstrated a high degree of agreement between different weighting schemes and index definitions. The sensitivity results, however, show that Tabouk and BTR/month had a significant impact on ranking stability. All things considered, the table offers a condensed numerical basis for the subsequent in-depth PCA, factor-analysis, clustering, and robustness interpretations.

Table 1. Important quantitative findings from PCA, HPI construction, clustering, and robustness validation

Analysis item	Quantitative result	What it means for the manuscript
Complete regional cases	16 health regions	Final multivariate model was based on complete regional observations
Indicators used	9 standardized indicators	BOR, PICU, ICU, NICU, BTR/month, ALOS, ER beds/100k, monitored ER beds/100k, diabetes visits/100k
PCA suitability	Bartlett $\chi^2 = 121.49$, $p = 3.36 \times 10^{-11}$	Correlation structure is suitable for PCA
Retained PCs	3 components	Employed for index construction
PC1 variance	38.25%	Central performance dimension
PC2 variance	33.08%	Secondary performance dimension
PC3 variance	11.39%	Additional readiness or demand dimension
Cumulative variance	82.72%	First 3 PCs captured most model statistics
HPI scale	0–100	PCA weighted index altered for interpretation
Highest HPI	Najran = 100.00	Powerful composite regional performance profile
Lowest HPI	Tabouk = 0.00	Lowest composite regional performance profile
Best cluster solution	$k = 3$, silhouette = 0.293	Three regional performance archetypes detected
Equal-weight vs PCA-weight HPI	Spearman $\rho = 0.924$, $p = 3.34 \times 10^{-7}$	HPI ranking robust to weighting method
PC1–PC2 vs PC1–PC2–PC3 rank stability	Spearman $\rho = 0.991$	Adding PC3 refined however not overturn rankings
Leave-one-variable sensitivity	Removing BTR/month: $\rho = 0.159$	BTR/month deeply influenced latent ranking structure
Outlier exclusion sensitivity	Excluding Tabouk: $\rho = 0.121$	Tabouk is the significant regional observation
Cluster stability	ARI = 1.000 for selected $k = 3$	Certain cluster solution is internally stable

In Figure 10, it assesses if the regional HPI is disproportionately driven by any single health region. Individually each bar reports the Spearman rank correlation between the original HPI ranking and the recalculated ranking upon removing one region at a time. Majority of exclusions preserve high rank correlation, indicates that it is not strongly dependent on a single observation and overall ranking structure is stable. When Tabouk is excluded, the largest sensitivity appears, which is suggesting that it contributes substantially to the lower end of the index distribution, and this region has a distinct performance profile. This test shows the

robustness of the regional ranking while it also identifies influential regions which require cautious interpretation.

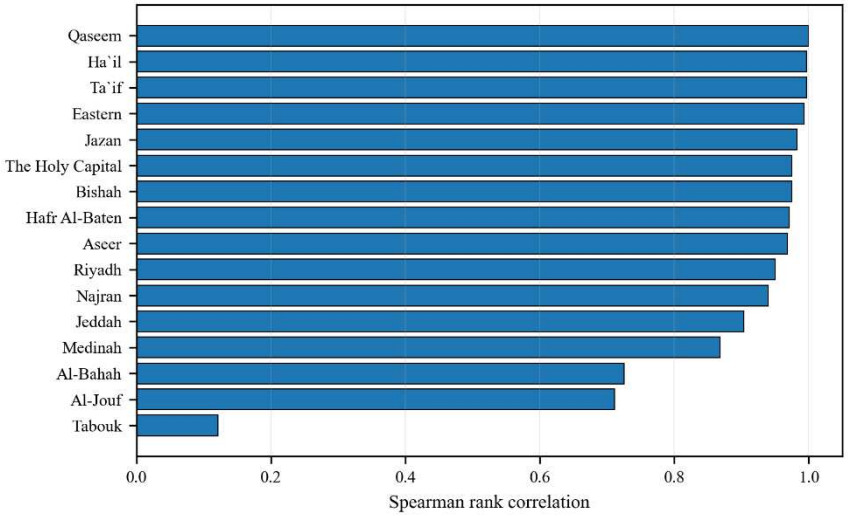

Figure 10. Outlier exclusion sensitivity

After excluding each indicator from the PCA model one at a time the Figure 11 illustrates the stability of the HPI. Correlations of High Spearman rank indicate even when individual variables are removed the regional ranking remains broadly consistent. ER monitored beds per 100,000 population, ER beds per 100,000 population show especially high stability, Diabetes visits per 100,000 population and ALOS, indicating that this index is not excessively dependent on these single indicators. Lower correlations for ICU, NICU, PICU and BTR/month indicate that these are the variables that contribute more strongly for the latent performance structure. This analysis will Benefits the methodological credibility of the composite index.

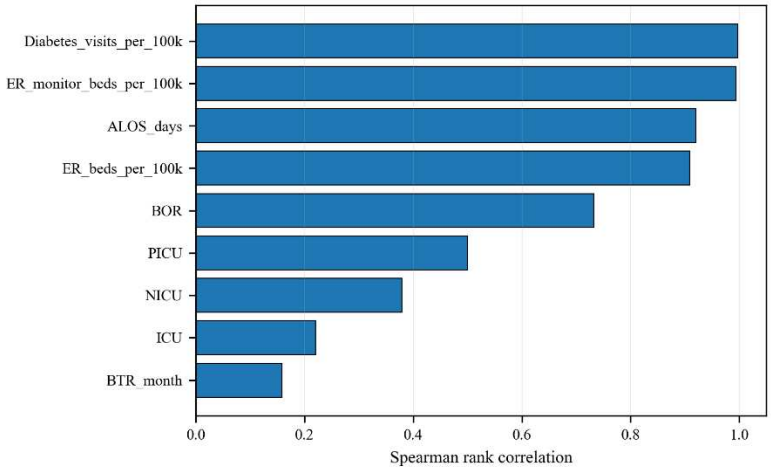

Figure 11. Robustness after excluding each indicator from PCA.

The scatterplot in Figure 12 makes the comparison between equal weighted standardized index and the PCA weighted HPI. This strong monotonic alignment indicates that the relative regional performance pattern is widely preserved under two different weighting strategies. Areas like Jazan and Najran will remain in the upper performance range, while Riyadh, Hafr Al-Baten and Tabouk remain lower. So this consistency indicates that the findings will not an artefact of PCA weighting alone. This plot also shows some dispersion within middle-ranked regions which indicates that fine-grained ordering will be more sensitive to weighting assumptions than the broad classification of low-performing and high-performing regional profiles.

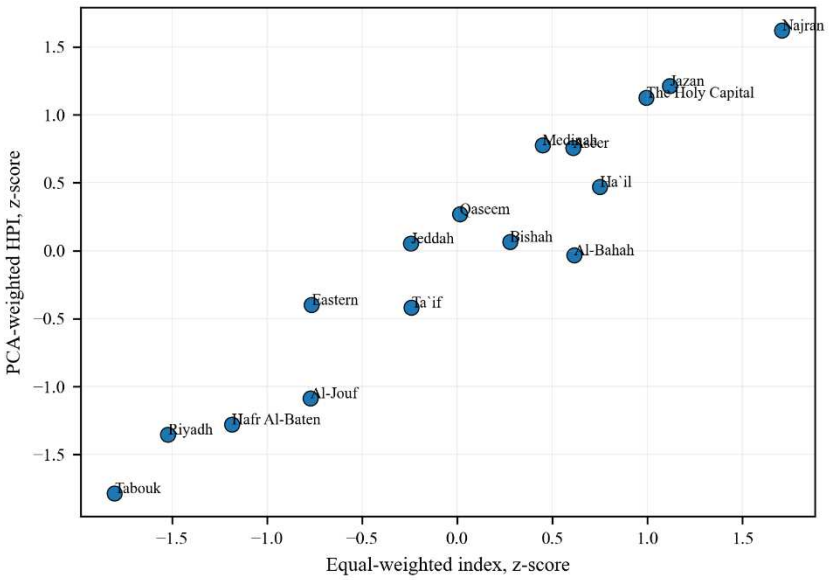

Figure 12. Equal weighted vs PCA weighted index

The comparison rank is made with the heatmap in Figure 13 by correlations among alternative index definitions: PC1-PC2-PC3, PC1-only and PC1-PC2.Regional rankings remain relatively stable across increasingly comprehensive PCA-based formulations is show by the high correlations. The PC1-PC3 and PC1-PC2 indices are especially similar indicating that by adding the third component refines instead of fundamentally changing the performance structure. Marginally lower agreement involving the PC1-only index will shows that relying only on the first dimension might omit relevant secondary information. As a result the PC1-PC3 weighted index is more defensible because it will captures multidimensional hospital performance as preserving ranking stability.

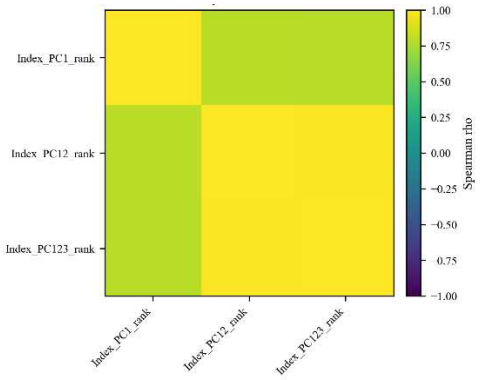

Figure 13. Heat map correlation for rank stability across index definitions

Comparison with the PC1-only index against the weighted PC1-PC3 HPI is done by using scatterplot in Figure 14. The first component that captures a major part of the regional performance gradient will be the positive association indicates. In contrast, the visible dispersion shows that PC3 and PC2 provide additional information, especially for regions with similar PC1 scores but different chronic-disease demand, specialized-care profiles or emergency-readiness. Areas like Jazan, the Holy Capital and Najran will remain high under the broader formulation, whereas Al-Jouf and Tabouk remain lower. This helps the use of a multidimensional index instead of simpler one-component score.

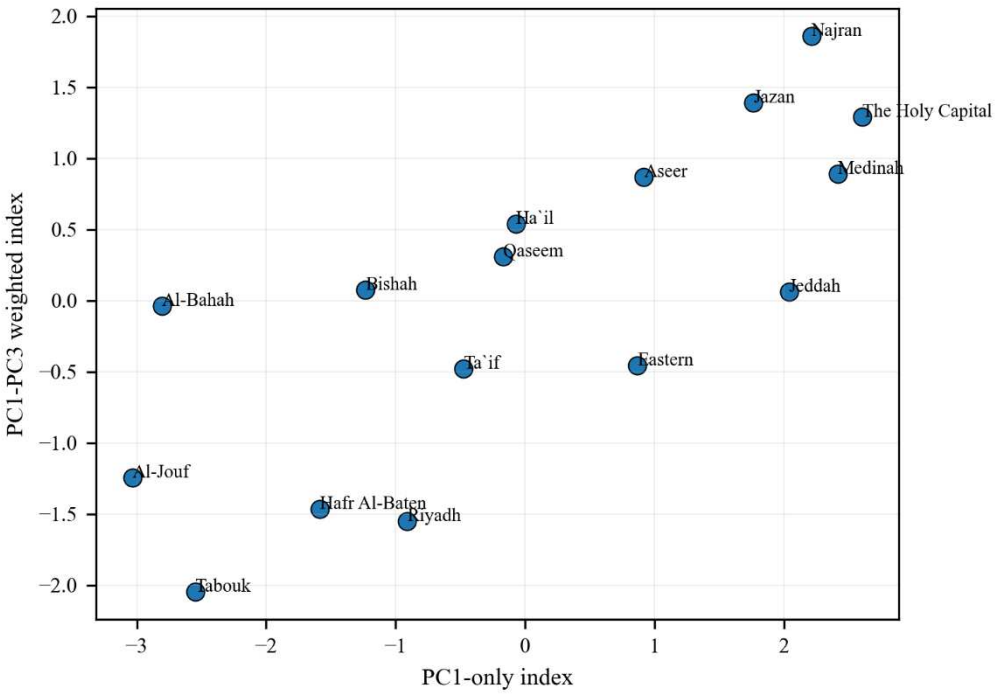

Figure 14 Index construction sensitivity

Similarity among health regions based on the retained PCA scores is visualized by the dendrogram (Figure 15). Regions joining at higher distances are more distinct where as regions that merge at lower Ward distances have more similar multivariate hospital performance profiles. The following diagram broadly supports the presence of multiple regional archetypes instead of single homogeneous national pattern. It supports the k-means clustering results by indicating how regions group with an alternative unsupervised method. Because similar groupings are visible without imposing the same partitioning algorithm, it strengthens the cluster interpretation.

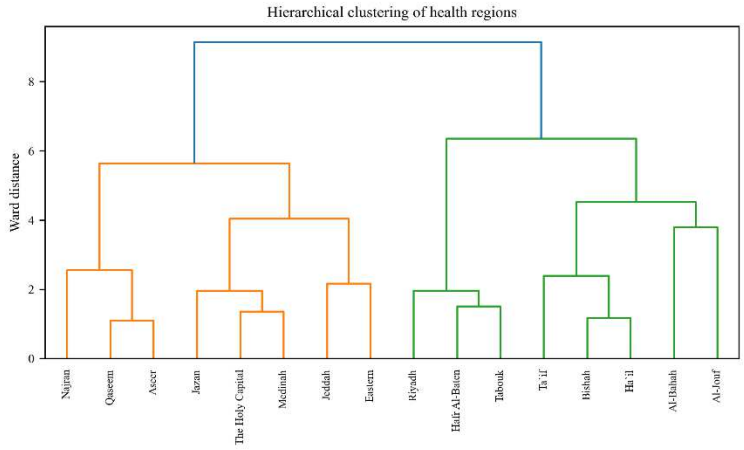

Figure 15. Health regions based on hierarchical clustering

By the interpretation of regional archetypes differ across hospital-performance dimensions, the heatmap in Figure 16 allows mean standardized indicator values for each cluster. Since the variables are z-scored, negative values indicate below-average characteristics and positive values indicate above-average cluster characteristics. Cluster 1 shows critical-care-related indicators and stronger utilization, whereas other clusters display occupancy-related measures, disease-service demand and different combinations of emergency readiness. The following figure is important because it converts the statistical clustering output into interpretable regional performance profiles suitable for policy discussion and it explains why clusters were formed, not merely which area belong to them.

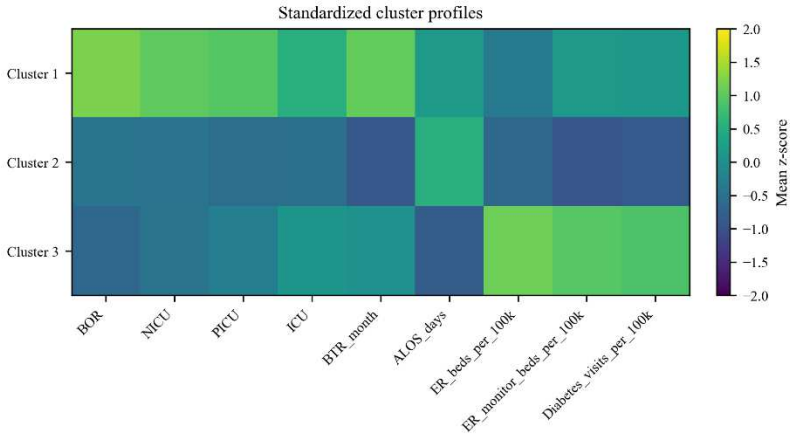

Figure 16. Cluster profiles mean z-score as per regional archetypes

The PCA score plot in Figure 17 shows regional clusters in the PC1-PC2 space. Saudi health regions can be classified into distinct performance archetypes based on their multivariate profiles and this separation is displayed with colored groups. Some of the clusters occupy areas associated with specialized-care capacity and higher utilization, while others are positioned toward more or lower demand-oriented performance profiles. Regional differences are multidimensional rather than reducible to one indicator is demonstrated in this figure. This supports factor analysis for identifying policy-relevant groups of health regions and the value of unsupervised learning as a complementary tool to PCA.

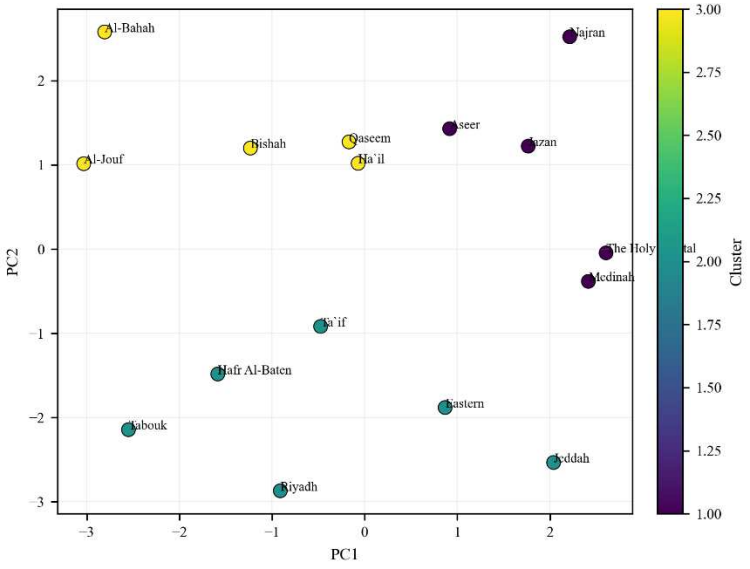

Figure 17. PCA scatterplot depicting cluster in PC1-PC2 region

The following Figure 18 positions every health region according to its first two principal component scores i.e., PC1 and PC2, PC1 captures the dominant performance gradient, whereas PC2 represents a secondary dimension separating regions with different capacity patterns, emergency-readiness or demand. Even if individual indicators may appear similar but the regions located far apart have different multivariate hospital profiles. Tabouk and Najran occupy opposite sides of the PCA space, consistent towards their contrasting HPI rankings. This demonstrates that the dimensionality reduction is useful for interpretation of complex hospital datasets as it provides an intuitive visual representation of latent regional variation.

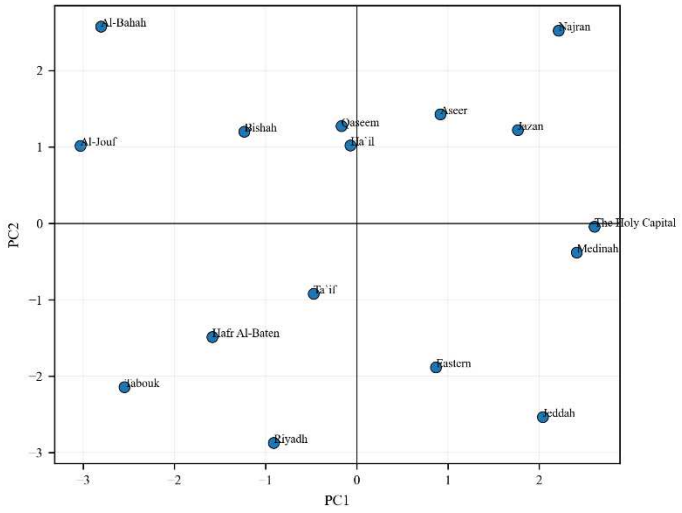

Figure 18. PCA space for regional distribution positioning every health region

By using bar chart illustrated in Figure 19, health regions are ranked from 0-100 HPI derived from the first three PCA components. Aseer, the Holy Capital, Najran, Medinah and Jazan show the strongest composite performance profiles, while Al-Jouf, Tabouk, Hafr Al-Baten and Riyadh occupy the lower range. Based on open-data indicators following rankings should be interpreted as relative system-level profiles, not as direct clinical quality rankings. This translates multiple hospital indicators into a single reproducible regional comparison.

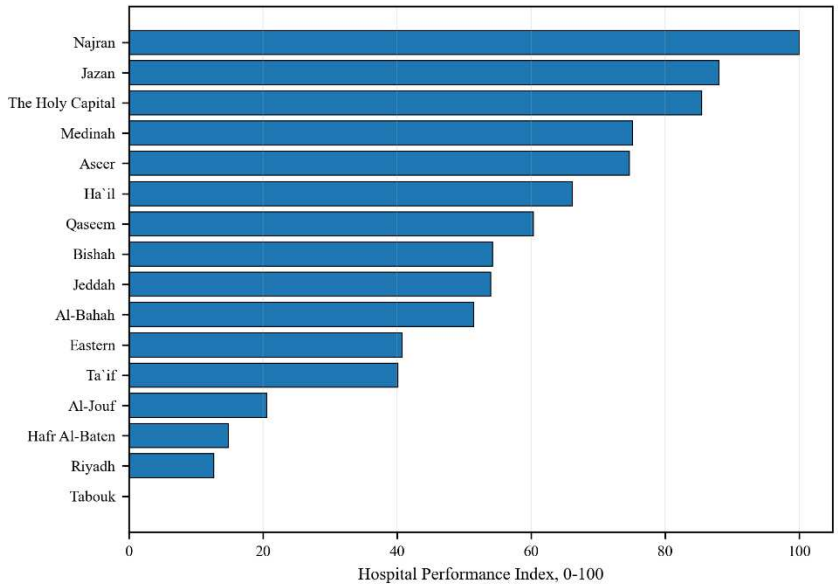

Figure 19. Performance based ranking of regional hospital

The varimax rotated factor analysis is presented in Figure 20. Rotating improves interpretability by concentrating high loadings under fewer factors. The first factor is dominated by BTR/month and BOR, suggesting a throughput and utilization dimension. The second factor is affected strongly by ALOS in the opposite direction, indicating an operational-pressure dimension or inpatient-stay. The third factor has diabetes-related measures and higher loadings for ER, reflecting service-demand structure and emergency readiness. This result complements PCA by giving a latent-factor interpretation.

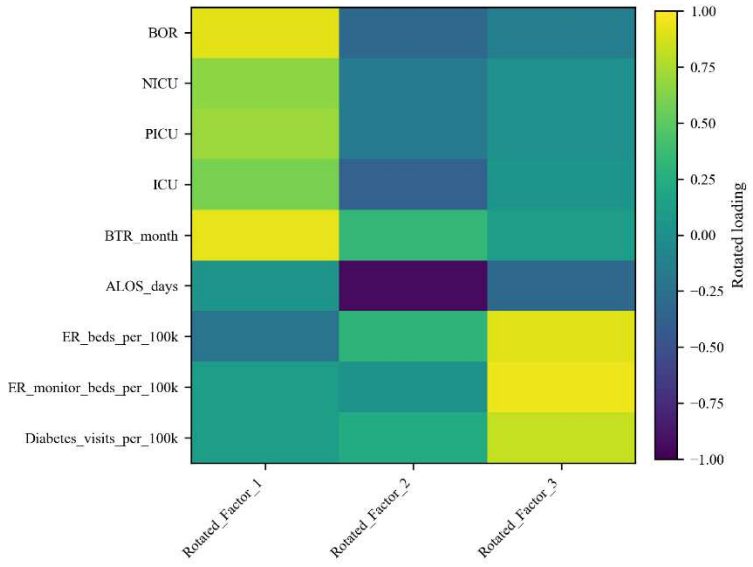

Figure 20. Rotated factors and loadings by varimax method

Table 2. Important latent factors found from varimax-rotated factor analysis

Latent factor	Significant variables	Key loading values	Interpretation
Factor 1	BTR/month, BOR, PICU, NICU, ICU	BTR/month = 0.933, BOR = 0.918, PICU = 0.703, NICU = 0.657, ICU = 0.597	Utilization throughput and critical care intensity
Factor 2	ALOS days	ALOS = −0.945	Inpatient stay pressure or length of stay dimension
Factor 3	ER monitored beds/100k, ER beds/100k, diabetes visits/100k	ER monitored beds = 0.950, ER beds = 0.906, diabetes visits = 0.825	Chronic disease service demand and population adjusted emergency readiness

The key latent factors supporting regional hospital performance are identified by summarizing the strongest loadings after varimax rotation. The important indicators that contribute to each factor are shown in Table 2, which also serves as the foundation for identifying the extracted dimensions.

The following Figure 21 shows the original factor-analysis loading matrix before rotation. The unrotated solution captures shared variance within observed indicators though it is less interpretable because several variables load over multiple factors. Critical-care indicators, BTR/month and BOR contribute towards the first factor whereas other service-related variables and ALOS show more complex patterns. This representation is for methodological reference as it provides clearer latent dimensions.

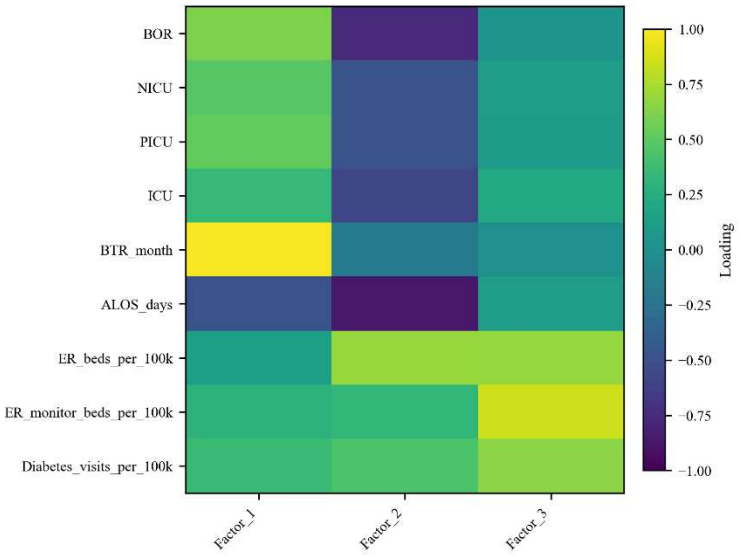

Figure 21. Before rotation factors and loading matrix

Figure 22 ranks indicators by its squared loading on PC1, representing its contribution to the dominant principal component. BOR contributes more strongly, followed by BTR/month, ICU, ALOS, PICU, ER beds per 100,000 population, and NICU. Monitored ER beds per 100,000 population contribute less to PC1 and Diabetes visits per 100,000 population. This indicates that PC1 is primarily a utilization and acute-care capacity dimension instead of chronic-disease demand dimension. The figure demonstrates which variables drive the main multivariate gradient among health regions and helps justify the interpretation of PC1.

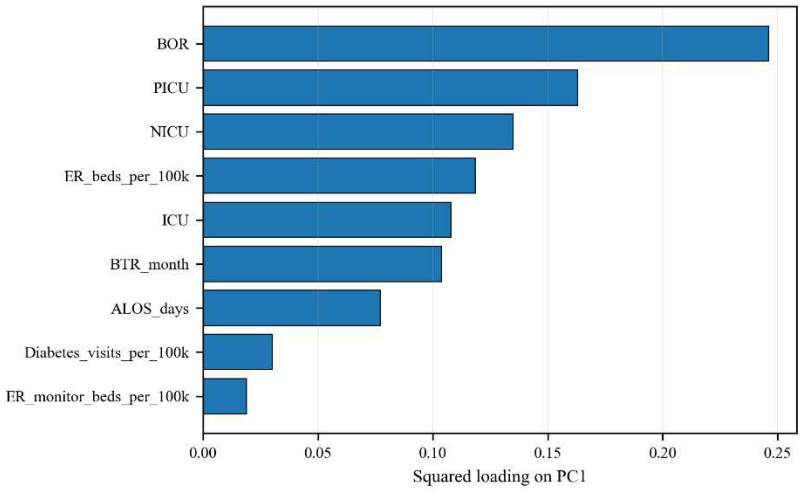

Figure 22. Indicators rank showing contribution to the dominant PC

The loading patterns of the first three principal components are displayed in Figure 23. PC1 is positively associated with ALOS, PICU, BTR/month, BOR, NICU and ICU, whereas showing negative association with diabetes visits per capita and ER beds per capita. PC2 is more strongly related to diabetes-service variables and ER-bed, whereas PC3 captures additional variation in ALOS and ICU. This validates that hospital performance is multidimensional. The decision to retain three components for index construction is supported because different components represent different aspects of regional hospital systems instead of repeating the same information.

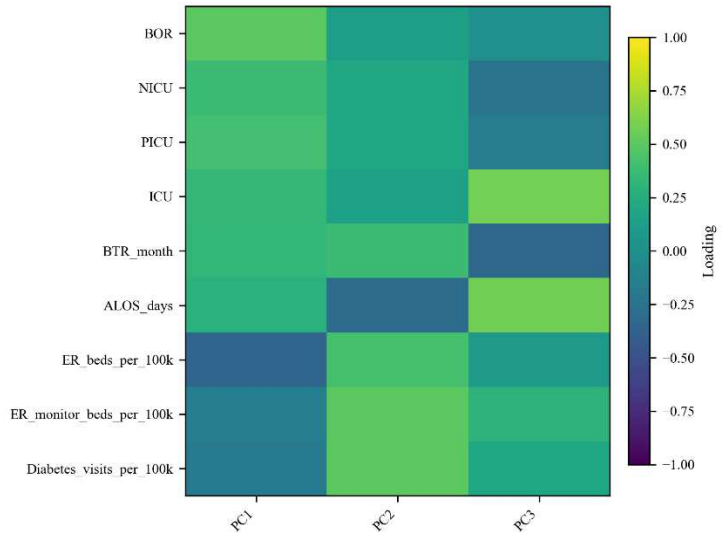

Figure 23. Loading structure of the PCA

Figure 24 shows the proportion of variance explained by the cumulative variance curve and each principal component. The first component explains the largest share. The first component describes the largest share, whereas the second component also contributes substantially, collectively, the first three components describes most of the multivariate variation within the regions, supporting their use in the HPI. Later on components contribute progressively are less useful for interpretation and smaller amounts of variance. Because a smaller number of components captures the dominant structure of the hospital-performance dataset while reducing redundancy among correlated indicators so this result will justify dimensionality reduction.

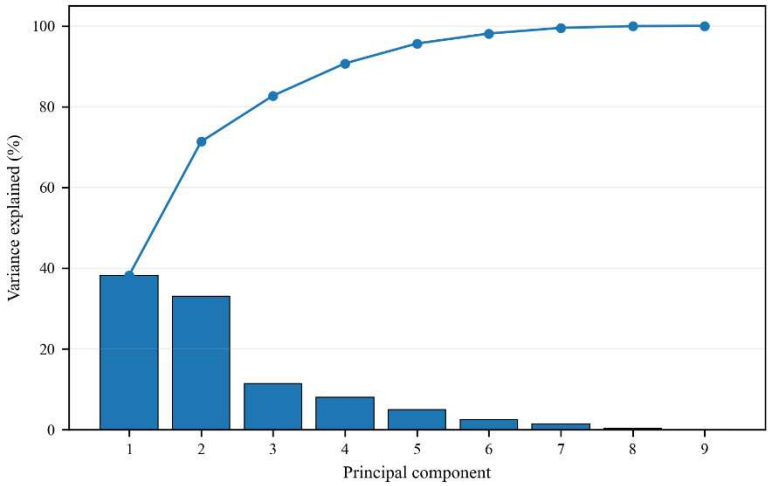

Figure 24. Proportion of variance by means of cumulative variance curve

The following Figure 25 summarizes pairwise Spearman correlations among hospital indicators. Stronger positive correlations among BTR/month, BOR, and specialized-care variables indicate that capacity-related measures and that utilization tend to move together across regions. Diabetes visits per population and ER-bed indicators show a different correlation pattern, suggesting that chronic disease service demand and emergency readiness represent separate dimensions. Some weaker or negative correlations indicate that not all hospital indicators reflect the same underlying construct. This correlation structure provides factor analysis and empirical justification for using PCA instead of isolated descriptive comparisons.

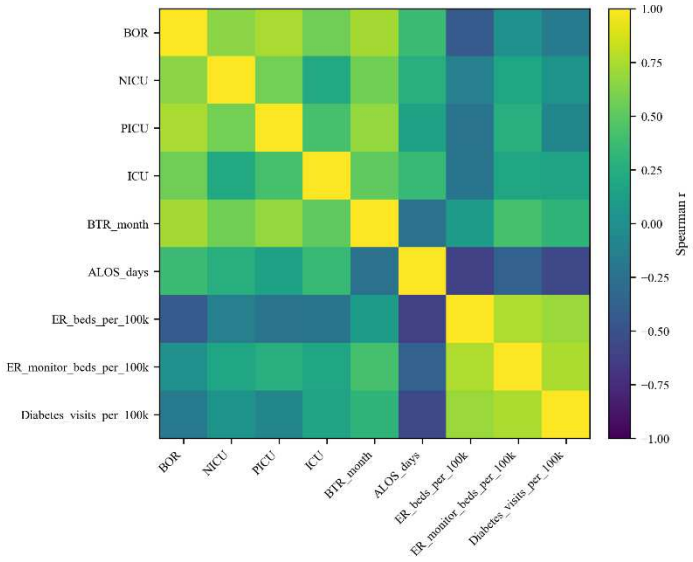

Figure 25. Spearman correlation structure

The stability of the selected cluster solution by using the adjusted Rand index over alternative numbers of clusters is evaluates in Figure 26. The most agreement occurs when this alternative solution uses three clusters, validating the three cluster structure selected. Forcing too few or too many groups changes regional membership substantially is indicated by lower values for two, four, or five clusters. By showing that the selected solution is not arbitrary this helps in robustness test which strengthens the clustering results. The interpretation of three major regional hospital performance archetypes indicates that cluster boundaries might shift under alternative specifications.

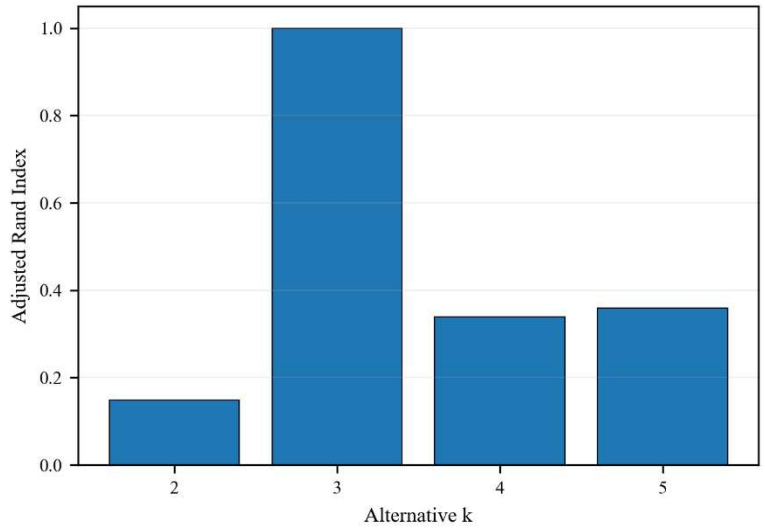

Figure 26. Adjusted Rand index to show the stability of cluster solution

Saudi health regions differ substantially in their multivariate hospital performance profiles is demonstrated by the results. Factor-analysis findings and the PCA shows that regional hospital performance is not a single dimensional construct; rather it reflects critical-care capacity, chronic disease service demand, inpatient-stay pressure, combination of utilization intensity and emergency readiness. The PCA-weighted HPI gives a reproducible summary measure whereas clustering reveals distinct regional performance archetypes. Robustness analyses show that the cluster interpretation and broad ranking are stable across outlier tests, alternative index definitions and variable exclusions. Although, because the data are region-level and ecological, the findings are system level performance patterns instead of direct patient level quality judgments.

In Table 3 the primary findings achieved from the analysis of regional data of Saudi hospital performance is indicated using the Multivariate method. PCA suitability, explained variance, preserved principal components, Hospital Performance Index findings, robustness validation and clustering output data are listed after the number of complete regional cases and indicators included in the final model. These findings demonstrate the multidimensionality, reproducibility, and statistical suitability of the suggested framework. The adoption of the first three primary components for index building is supported by the fact that they accounted for 82.72% of the total variance. The clustering analysis divided Saudi health regions into three performance archetypes, while the HPI results showed Tabouk as the lowest-ranked region and Najran as the highest-ranked region. Although BTR/month and Tabouk had significant

sensitivity, robustness studies further demonstrated that the overall results were consistent across different weighting and index definitions.

Table 3. Key quantitative findings through factor analysis, PCA, HPI construction, robustness validation and clustering.

Result domain	Main numerical finding	Discussion interpretation
PCA dimensionality	PC1 = **38.25%**, PC2 = **33.08%**, PC3 = **11.39%**, cumulative = **82.72%**	Hospital performance is strongly multidimensional; these components are sufficient to summarize most of the regional variation
Factor 1	BTR/month = **0.933**, BOR = **0.918**, PICU = **0.703**, NICU = **0.657**, ICU = **0.597**	Regions having high scores on this factor combine faster turnover, higher utilization, and stronger critical care intensity
Factor 2	ALOS = **−0.945**	The Length of stay is a separate inpatient stay pressure dimension instead of simply following occupancy/turnover
Factor 3	ER monitored beds/100k = **0.950**, ER beds/100k = **0.906**, diabetes visits/100k = **0.825**	Emergency readiness and chronic disease assistance request formed a population adjusted readiness/demand dimension
HPI upper range	Najran = **100.00**, Jazan = **88.06**, Holy Capital = **85.50**, Medinah = **75.17**, Aseer = **74.68**	Here the regions show a stronger composite profile around the available open data indicators
HPI lower range	Tabouk = **0.00**, Riyadh = **12.66**, Hafr Al-Baten = **14.82**, Al-Jouf = **20.58**, Ta'if = **40.16**	Here these regions occupied the lower end of the composite system level performance profile
Clustering	Best k = **3**, silhouette = **0.293**	Three regional archetypes are identified, supporting heterogeneity instead of one uniform national profile
Robustness	Equal-weight vs PCA-weight ρ = **0.924**, p = **3.34×10^{-7}**	Broad findings are not only an artifact of PCA weighting
Rank stability	PC1–PC2 vs PC1–PC2–PC3 ρ = **0.991**	The 3rd component refined rankings, however, did not noticeably change the main ordering
Sensitivity	Removing BTR/month ρ = **0.159**; excluding Tabouk ρ = **0.121**	Turnover and Tabouk distinct's regional profile should be discussed cautiously as prominent elements
Cluster validation	ARI = **1.000** for selected k = 3	The selected cluster solution is stable under the validation comparison

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Conclusion

This study demonstrates that multivariate statistical techniques could transform Saudi open government hospital datasets into a rigorous regional performance assessment framework by rotated factor analysis, clustering, robustness testing, integrating PCA, spatial interpretation and composite indexing. This analysis gives a multidimensional view of hospital system performance across health regions. It shows that regional hospital performance cannot be adequately represented by a single raw indicator, instead, it shows population adjusted service demand, inpatient pressure, interacting dimensions of capacity, utilization and emergency readiness. The proposed cluster profiles and HPI gives practical tools for benchmarking, supporting evidence-informed resource planning and identifying regional performance archetypes. Significantly, the index is a system level hospital performance measure instead of direct patient level quality-of-care outcome, because the available infrastructure indicators and open data primarily capture service activity. Upcoming research should extend this framework by incorporating hospital accreditation outcomes, region-specific expenditure, waiting times, patient safety indicators, staffing ratios, mortality, patient satisfaction, readmission and infection rates. Connecting open administrative data with clinical outcome datasets might allow stronger causal and efficiency analyses. For longitudinal monitoring to evaluate the impact of Saudi health sector transformation initiatives over time this framework can also be adapted.

Declarations

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Ethics approval and consent to participate: not applicable

Authors' contributions: Mohammed Al Awadh – Writing original manuscript, methodology, data curation, conceptualization.

Competing Interests: not applicable

Availability of data and materials: The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Consent for publication: not applicable

Abbreviation	Full form
AI	Artificial intelligence
ALOS	Average length of stay
ARI	Adjusted Rand index
BOR	Bed occupancy rate
BTR/month	Bed turnover rate per month
EFA	Exploratory factor analysis
ER	Emergency room
FA	Factor analysis
HPI	Hospital Performance Index
ICU	Intensive care unit
ISI	Insomnia Severity Index
MoH	Ministry of Health
NICU	Neonatal intensive care unit
OGD	Open Government Data
OHBI	Organizational Health Behavior Index
PC	Principal component
PCA	Principal component analysis
PICU	Pediatric intensive care unit

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