Analyzing the Efficiency of Moroccan Hospital Network Regions via DEA and Tobit Regression: Assessing DEAP 2.1 Software versus Generative AI ChatGPT 3.5

Analyse de l'Efficacité des Régions du Réseau Hospitalier Marocain via DEA et Régression Tobit : Évaluation du Logiciel DEAP 2.1 par Rapport à l'IA Générative ChatGPT 3.5

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Abstract

Context: Optimising hospital establishment efficiency, especially in staffing and resource utilization, is crucial for achieving SDG 3 objectives like quality healthcare services, universal health coverage, and individual well-being.

Objectif: This study aims to assess the technical efficiency of hospital networks in each health directorate region in Morocco and analyze the impact of staff personnel health on inefficiency.

Method: The study uses Data Envelopment Analysis Programming (DEAP) software version 2.1 and generative Artificial Intelligent ChatGPT 3.5 to analyze 12 hospital network health directorate regions. Tobit regression was employed to analyze the impact of worker health and hospital activity on inefficiency. **Results and discussion:** showed that the average technical efficiency was more inefficient in generative AI ChatGPT 3.5 than in DEAP software version 2.1. Hospital activity and nurse staffing significantly impacted inefficiency levels. **Conclusion:** The study concludes that inefficiency in hospital networks and staff personnel health pose challenges for managers in health directorate regions, emphasizing the need for New Public Management principles based on contractualization, accountability, and managerial practices.

Keywords: Hospital network; Data Envelopment Analysis; Tobit regression; DEAP software, ChatGPT 3.5.

Résumé

Contexte : L'optimisation de l'efficacité des établissements hospitaliers, notamment en matière de dotation en personnel et d'utilisation des ressources, est essentielle pour atteindre les objectifs de l'ODD 3 tels que la qualité des services de santé, la couverture sanitaire universelle et le bien-être individuel.

Objectif : Cette étude vise à évaluer l'efficacité technique des réseaux hospitaliers dans chaque région sanitaire du Maroc et à analyser l'impact de la santé du personnel sur l'inefficacité. **Méthode :** L'étude utilise le logiciel d'analyse par enveloppement des données (DEAP) version 2.1 et l'intelligence artificielle générative ChatGPT 3.5 pour analyser 12 régions sanitaires du réseau hospitalier. Une régression Tobit a été utilisée pour analyser l'impact de la santé du personnel et de l'activité hospitalière sur l'inefficacité. **Résultats et discussion :** Les résultats ont montré que l'efficacité technique moyenne était plus faible avec l'IA générative ChatGPT 3.5 qu'avec la version 2.1 du logiciel DEAP. L'activité hospitalière et les effectifs infirmiers ont eu un impact significatif sur les niveaux d'inefficacité.

Conclusion : L'étude conclut que l'inefficacité des réseaux hospitaliers et la santé du personnel posent des défis aux gestionnaires des régions sanitaires, soulignant la nécessité d'adopter des principes de nouvelle gestion publique fondés sur la contractualisation, la responsabilisation et les pratiques managériales.

Mots-clés : Réseau hospitalier ; analyse par enveloppement des données ; régression Tobit ; logiciel DEAP ; ChatGPT 3.5.

Introduction

Background

Hospitals are vital in achieving Sustainable Development Goal 3's "Good Health and Well-Being" by providing essential healthcare services across various health domains, ensuring access to skilled professionals and necessary medical interventions, and contributing to universal health coverage. (UN, 2020; WHO, 2019, 2023).

Optimising hospital establishment efficiency, especially in staffing and resource utilization, is crucial for achieving SDG 3 objectives like quality healthcare services, universal health coverage, and individual well-being. However, in African nations, lack of financing, healthcare access disparities, prolonged waiting times, and delayed use of GAI are significant challenges. (Er-Rays & Midoud, 2024).

Morocco's 60% health budget for hospital networks is crucial for monitoring technical efficiency. This helps maximize patient care, minimize costs, enhance staff satisfaction, adapt to changing demands, and make data-driven decisions, contributing to SDG 3 targets and promoting good health and well-being (En-Naoui et al., 2024).

Morocco has made significant progress in achieving the SDG 2030, focusing on good health and well-being, no poverty, and zero hunger. The maternal mortality ratio has improved to 72 per 100,000 live births, while the under-5 mortality rate has declined to 18 per 1,000 live births. However, the adolescent fertility rate remains low, indicating the need for continued efforts to ensure access to reproductive healthcare and education. Morocco faces challenges in addressing poverty and inequality (WB, 2023). Morocco has made also significant strides in poverty reduction, with a poverty headcount ratio of 1.4% of the population in 2013 and a national poverty line ratio of 4.8%. However, more efforts are needed to address remaining poverty and inequality, as Morocco faces significant challenges in addressing its poverty and inequality. (WB, 2023).

Morocco faces challenges in the realm of zero hunger, but also shows progress. The prevalence of stunting, which reflects chronic malnutrition in children under 5, remained at 14.2% in 2019, indicating that a significant portion of children experience growth faltering (WB, 2023). However, efforts to combat undernourishment have shown promise, with only 6% of the population experiencing it as of 2021. Moreover, the prevalence of stunting, disaggregated by gender, shows relatively balanced rates among male and female children. These findings underscore the importance of continued investments in nutrition programmes and food security initiatives to ensure all Moroccans have access to adequate nutrition and achieve optimal health outcomes.

Up to day

Measuring the performance of healthcare systems requires the development of a conceptual framework to model system components and identify key performance indicators (Smith, Mossialos, Papanicolas, & Leatherman, 2012). This process assists stakeholders in pinpointing the information required for effective evaluation and streamlines the selection of appropriate performance metrics (Vrijens et al., 2014).

In the late 1970s, William W. Cooper, Lawrence M. Seiford (Cooper et al., 2004), and Kaoru Tone developed Data Envelopment Analysis (DEA), a non-parametric method, to measure the efficiency of decision-making units (DMUs) that convert multiple inputs into multiple outputs (Debreu, 1951) and (Koopmans, 1951).

It compares DMUs' performance to a hypothetical best-practice frontier, allowing for the assessment of relative efficiency without explicit assumptions about the underlying production process or functional form. Various fields such as economics, operations research, management science, and healthcare widely apply DEA (Cooper et al., 2000a, 2000b, 2011a, 2011b; Seiford, 1996).

Many studies show that hospitals in African countries have a low score on technical efficiency. The low levels of technical efficiency in hospitals exacerbate resource scarcity and hinder efforts to provide accessible, high-quality healthcare services in many countries (Africa WHO, 2023; Arhin et al., 2023; Babalola et al., 2022; Ibrahim et al., 2019; M. Kirigia Joses, 2015; Musoke et al., 2023). The studies conducted in Morocco (Er Rays & Ait-Lemgeddem, 2020; Er-Rays, 2021a; Er-Rays, Ait-Lemgeddem, et al., 2024; Er-Rays, Midloud, & Ait-Lemageddem, 2024; Er-Rays, Midloud, Ait-Lemgeddem, et al., 2024; Er-Rays & Ait Lemageddem, 2020b; Er-Rays & MDloud, 2024), Benin (Asbu et al., 2003), Ethiopia (Ali et al., 2017), Burkina Faso (Marschall & Flessa, 2009), Botswana (Tiotlego et al., 2010), and Eritrea (J. M. Kirigia & Asbu, 2013). Additionally, research has been carried out in specific regions such as KwaSulu-Natal Province, South Africa (Babalola et al., 2022); Ghana (Vukey et al., 2023); northwestern Ethiopia (Lamesgen et al., 2022); and Uganda (Mujasi et al., 2016), Egypt (Habib & Shahwan, 2020).

For example, Asbu et al. conducted a study to assess the changes in productivity of some hospitals in Benin over five years, using the Malmquist data envelopment analysis method. Through physical visits, they collected health inputs and utilisation data from the records of sampled hospitals (Asbu et al., 2003). Marschall et Flessa proposed a study to evaluate the relative efficiency of health centres in rural Burkina Faso and investigate reasons for inefficient performance. They used data envelope analysis (DEA) to account for the situation in that country and applied the Tobit model to identify the spatial effect of the catchment area on efficiency (Marschall & Flessa, 2009). Another study for Kirigia and Asbu (2013), whose used Tobit regression analysis to figure out how inefficient public secondary level community hospitals in Eritrea are in terms of technical and scale. They also figured out how much output and/or input reductions would have to happen for hospitals to become more efficient, and they found out how institutional and contextual/environmental variables affected hospital inefficiency (J. M. Kirigia & Asbu, 2013). As for Babalola and his colleagues used data from 38 public district hospitals in KwaSulu-Natal province from 2014/15 to 2016/17. They used both constant return to scale (CRS) and variable return to scale (VRS) models to determine the technical efficiency of the hospitals.

Among these studies is the use of data envelope analysis (DEA) as the primary method for assessing efficiency. DEA allows researchers to evaluate the relative efficiency of healthcare facilities by comparing their input-output relationships. Regarding input and output variables, there is variation among the studies based on the specific context and objectives. Inputs commonly include factors such as non-salary recurrent costs, salary costs, the number of beds, and health resources. Outputs typically consist of measures related to patient care, such as neonatal admissions, outpatient visits, referrals, bed occupancy rates, average length of stay, and bed turnover rates. The analysis's orientation also differs. Some studies adopt an output-oriented approach, focusing on maximising outputs given a set of inputs. Others may take an input-oriented approach, seeking to minimise inputs while maintaining a certain level of output. Additionally, some studies explore both technical and scale efficiency, while others focus on total factor productivity or assess changes in efficiency over time using methods like the Malmquist productivity index. Despite these differences, the common thread of utilising DEA for efficiency analysis, along with consideration of inputs, outputs, and analysis orientation, underscores the importance of this method in evaluating healthcare system performance across diverse contexts.

Generally, the majority of these studies concentrate on the first stage, assessing the efficacy of either hospital-provided curative care or primary healthcare settings' preventive care. However, there remains a notable gap in the research relating to the second stage of the analysis. This phase involves comprehensively evaluating hospitals while exploring the determinants of technical efficiency or inefficiency, often using panel data methodologies. Although this study focuses on the first and second stages of DEA analysis, it is critical to acknowledge the broader landscape of research in this area.

Each study in this area adapts its approach based on the available data and the researchers' perspectives regarding the selection of input and output variables. This customisation allows for a nuanced examination of hospital effectiveness, taking into account the unique characteristics and objectives of different studies.

Additionally, it is essential to recognise the critical link between the quality of patient care and population health outcomes. Improvements in patient safety and the efficiency of hospital healthcare delivery systems have contributed significantly to improvements in overall population health metrics. The observed increase in life expectancy and decrease in infant mortality rates demonstrate this positive impact, underscoring the interdependence between hospital system performance and broader public health outcomes.

The study aims to address research gaps in understanding healthcare hospital system efficiency in Morocco, a country with dysfunctional regional healthcare disparities. The majority of healthcare hospitals are located in a minority of health directorate regions (HDR), such as Rabat-Sale-Kénitra, Casablanca-Settat, and Marrakech-Safi HDR. The Data Envelopment Analysis (DEA) method and its components are not used to assess the technical efficiency of hospital networks (HN) in each HDR.

To frame the research approach, the study adopts a dual methodological perspective based on the nature of the research question. The problematic aligns with the positivism paradigm, necessitating a quantitative study. This involves using a guide to explore and validate propositions regarding the use of DEAP Software version 2.1 and GAI ChatGPT 3.5 to improve HN efficiency in each HDR in Morocco, leveraging health economics, econometrics, accounting, and computer sciences.

The study aims to stimulate discovery and innovation in healthcare efficiency by providing researchers with current information on improving Moroccan hospital performance. It contributes to exploring the integration of Generative Artificial Intelligence (GAI) in monitoring hospital efficiency and its potential applications in Moroccan settings.

Brief country profile

Morocco, a country in North Africa and the Middle East, falls into the middle-income category, a lower segment. This economic position reflects both the challenges and opportunities the country faces. Despite its strategic geographical location and rich cultural heritage, Morocco faces obstacles such as unemployment, poverty, and socio-economic inequalities. However, the Moroccan government is implementing policies aimed at stimulating economic growth, diversifying productive sectors, and improving access to education and health services. These efforts aim to create an environment conducive to sustainable development and social inclusion in order to promote a more prosperous future for all Moroccan citizens.

Morocco's healthcare system has undergone several phases over the years, reflecting evolving priorities and challenges (Errami & Cargnello, 2016; Harfaoui et al., 2024).

From 1959 to 1980, the focus was on establishing the national health system, with infrastructure development, nationalisation of resources (Ministry of Health, 2013), and initiatives against epidemics being key. Notable milestones included the creation of medical facilities, vocational training schools, and delegating healthcare responsibilities to local authorities (Espace, 2015).

From 1981 to 1995, Morocco emphasised primary healthcare, extending services, strengthening basic health structures, developing health programmes, and adopting health promotion measures. Major restructuring efforts in 1994 laid the groundwork for hospital reform, including the creation of central directorates (Ministry of Health & WHO, 2016).

Between 1996 and 2010, Morocco embarked on significant healthcare reforms, focusing on regionalisation and financing. Morocco fostered partnerships to enhance regionalisation, hospital reform, and health insurance. We initiated major projects aimed at improving hospital management, care quality, and sector financing. Legislative changes, such as Law 65 – 00, facilitated the implementation of reforms, including the Basic Medical Coverage (BMC) reform (Er-Rays & Ait-Lenngeldem, 2021; Harfaoui et al., 2024; Hazimi, 2006; Ministry of Health, 2008; UNDP, 2016).

From 2011 to 2019, Morocco focused on developing the right to health in new constitution 2011 and further reforming the healthcare system. International commitments to SDG and programmes aimed at equitable access and quality improvement were prominent. The COVID-19 pandemic prompted mobilisation efforts and further healthcare system reforms (Constitution, 2017 ; La Loi Cadre N° 34 – 09 Relative Au Système de Santé Et À L'offre de Soins PDF | PDF, s. d.; IRES, 2022).

Morocco is undergoing a new phase of reform from 2020 to 2024, aiming for a more efficient and equitable healthcare system. Royal directives in 2020 called for a system overhaul, while legislative measures like Framework Law 09–21 (Official Bulletin No. 6975: Implementing Framework Law no. 09.21 on Social Protection (2021), 2021) and Reform 06.22 (Official Bulletin No. 7178: Promulgating Framework Law No. 06–22 Relating to the National Health System, 2023) facilitate social security coverage generalisation and system reorganisation.

In 2022, new reforms were implemented, including the reform aimed at improving the productivity of HNs for each region, namely: the National Health System, the creation of Territorial Health Groupings (Law No. 08–22 Relating to the Creation of Territorial Health Groups. (2023), 2023), the establishment of the Health Function (Law No. 09–22 Relating to Healthcare Employment. (2023), 2023), the creation of the Moroccan Agency for Medicines and Health Products (Law No. 10–22 Relating to the Creation of the Moroccan Agency for Medicines and Health Products, 2023), the creation of the Moroccan Blood Agency and its derivatives (Law No. 11–22 Relating to the Creation of the Moroccan Agency for Blood and Blood Products. (2023), 2023), the establishment of the High Authority for Health (Law No. 07.22 Establishing the High Authority for Health. (2023), 2023), and the complete revision of the responsibilities, functions, and organisation of the central administration. While the Ministry of Health and Social Protection reorganisation aims to improve system quality and efficiency, improvement of healthcare facilities, both hospitals and primary healthcare, generalisation of medical coverage, rehabilitation of healthcare provision, strengthening of the budget of the Ministry of Public Health and Health, digitisation of the healthcare system, consolidation of health programs and epidemiological surveillance, enhancement of access to medicines and healthcare products, and assessment of digital communication activities.

The funding, legal framework, and health segmentation determine the structure of the HN in Morocco.

Hospital funding is based on a combination of public resources from the state budget as well as private funding and health insurance.

With regard to the legal framework, health areas are defined by articles 17, 18, and 19 of Decree 2-14-562. They correspond to the regions' territories, as defined by the Kingdom's administrative division. Each health region consists of two or more health prefectures and provinces and is the field of intervention of the Regional Health Directorate under the Ministry of Health (Health Card - Situation of health care provision - Year 2022: Health care provision, 2022) (Er-Rays & Ait Lenngeldem, 2020b; Er-Rays & M'Dioud, 2024).

In terms of hospital care, the HN's health facilities include different types of facilities, such as prefectural and provincial hospitals, regional hospitals, and interregional hospitals. Psychiatric hospitals include regional, oncology centres, hemodialysis centres, neighbourhood hospitals, day clinics, excellence centres, and reference centres. There are also specialised support structures for hospital facilities, such as the National and Regional Centre for Blood Transfusions and Haematology, the National Institute of Hygiene, the National Centre for

Poisoning and Pharmacovigilance, and the National Centre for Radiation Protection (Health Card - Situation of health care provision - Year 2022: Health care provision, 2022).

In terms of public hospital infrastructure in 2022, there were 159 hospitals with 25,889 beds, 11 psychiatric hospitals with 1,512 beds, and 131 hemodialysis centres equipped with 2,739 dialysis devices (Health, 2022).

In analysing the production indicators of public hospitals in Morocco, several key metrics shed light on healthcare provision and resource utilisation (Table 4). With a total population of 37,140,944, the Ministry of Health and Social Protections budget for 2022 stands at 23,542,550,000 Moroccan Dirham (DH), representing 7.14% of the total state budget. Despite this, the global budget, as a percentage of GDP, is 1.76%. Hospital capacity, both functional and existing, is significant, with 21,455 and 27,401 beds, respectively. Admissions totaled 1,043,904, with 4,289,970 hospitalisation days and 300,162 surgical interventions (Health, 2022). Outpatient consultations average 613 per physician, while caesarean section rates stand at 18%, with instrumental and non-instrumental low-path deliveries at 37.3% and 44.7%, respectively. The average occupancy rate is 60.8%, with a mean length of stay of 4.1 days and a turnover rate of 48.7%. Each physician performs an average of 154 surgical interventions (Health, 2022). These indicators collectively offer insight into the performance and efficiency of Morocco's public hospital system in delivering healthcare services to its population.

The organisation of this paper was as follows: the next section (Section 2) presents the method adopted to develop this model by presenting the DEA method and Tobit regression steps. Section 3 describes the results of testing these two stages in a Moroccan public HN. Section 4 provides a discussion of the results.

1. Method

1.1. Study design

This study selected Moroccan HN for each HDR, which based on the administrative divisions criteria. The HN includes local, provincial, regional, and academic facilities. The Ministry of Health, 2022, gathered data sets from a total of 12 hospitals within the network (Ministry of Health, 2022). The inputs include the number of hospitals in each HDR, as well as the number of doctors, specialist doctors, nurses, and midwives. The outputs consist of hospital activities, specialised consultations, public hospital laboratory activities, and surgical services (Tables 1).

Table 01 : variable and justification

Variable	**Justification of Inputs and Outputs Variables**
Inputs (Ministry of Health, 2022)	
Hospital	Hospital facilities significantly impact healthcare operations by enhancing patient experience, facilitating workflows, and supporting staff in delivering quality services.
Physicians	General Practitioners, specialist doctors, pharmacists, and dentists play crucial roles in primary healthcare, managing medical conditions, influencing patient access, ensuring safe medication use, optimizing therapeutic outcomes, and enhancing patient care quality.
Nursing Staff	Healthcare staff, including nurses, midwives, and other healthcare professionals, provide patient care, administer treatments, and monitor patient status.
Populations in each province	Population demographics and health needs are crucial for effective planning, resource allocation, and service provision. Population data informs facility location, staffing, service expansion, and community outreach initiatives, enhancing healthcare access, equity, and efficiency.
Outputs	
Hospital Activity	Assessing resource allocation efficiency in healthcare facilities involves evaluating bed capacity, hospitalization days, admissions, occupancy rates, turnover rates, and length of stay, with shorter stays indicating streamlined processes.
Specialised Consultations	The availability of specialized doctors and the efficiency of specialist consultations are crucial factors in a facility's ability to meet patient needs, ensuring timely access to specialized care and enhancing the overall service quality.
Public Hospital Laboratory Activities	Public Hospital Laboratory Activities include comprehensive tests like bacteriology, parasitology, and immunosetology, as well as tracking sample volumes to ensure accurate diagnoses and effective treatment plans, enhancing efficiency.
Surgical Services(Ministry of Health, 2022)	Public Hospital Laboratory Activities include comprehensive tests like bacteriology, parasitology, and immunosetology, as well as tracking sample volumes to ensure accurate diagnoses and effective treatment plans, enhancing efficiency.

1.2. Dataset

This study utilized the dataset from Morocco's Ministry of Health and Social Protection (Health, 2022) to ascertain the efficiency of the HN in each HDR. The 12 HN comprise 159 hospitals, totaling 25,889 beds, distributed across 12 HDR (Health, 2022).

1.3. First Stage

DEAP software for calculating DEA: CRS versus VRS

Measure efficiency use two frontier methodologies, stochastic frontier analysis (SFA) and data envelopment analysis (DEA). In 1957, Farrell laid the groundwork for efficiency measurement methodology and principles (Farrell, 1957). Establishing the best-practice production frontier (isoquant) and assessing each decision-making unit (DMU) against it is a fundamental aspect of evaluating efficiency. Aigner, Lovell, and Schmidt introduced the Stochastic Frontier Analysis (SFA) method in 1977 (Aigner et al., 1977) and Meeusen and Van den Broeck (1977) (Meeusen & Van Den Broeck, 1977). Charnes et al. introduced the Data Envelopment Analysis (DEA) method (Charnes et al., 1978), utilising distinct techniques to envelop data, such as statistical or mathematical programming (Linh Pham Thuy, 2011).

There has been a long-standing discussion on measuring technological efficiency in health facilities, but there has been no agreement on the optimal approach for quantifying frontier efficiency in hospitals. This study used the DEA approach to evaluate the effectiveness of Morocco's HN for two specific purposes. DEA is most appropriate in low-income nations with inadequate health sector information, namely, lacking data on hospital input and output pricing. Additionally, DEA is less reliant on extensive data compared to econometric approaches. It does not necessitate a large sample size, information on input and output prices, or the conversion of physical units into a single unit of measurement. Nevertheless, it is susceptible to outliers and measurement errors.

DEA is a mathematical programming-based technique used to evaluate the relative performance of organisations. While not-for-profit organisations have been its primary application, DEA can also successfully compete with techniques such as cost-benefit analysis and multi-criteria decision-making in other contexts. Charnes et al. introduced DEA in 1978, drawing its roots from earlier works (Farrell, 1957) and (Koopmans, 1951). Even in the original constant returns to scale (CRS) models, which assume proportionality, DEA, often presented as a non-parametric technique, relies on the assumption of linearity. DEA identifies both efficient and inefficient units within a specific context, allowing for comparisons among units while considering various factors. The technique also identifies "peer groups" of efficient units that serve as role models for inefficient units, helping to identify best practices.

Constant Returns to Scale (CRS) Model:

The CRS model assumes that the production process exhibits constant returns to scale (Cooper et al., 2000b, 2007). To put it another way, scaling up or down the inputs proportionately does not affect the output. This model facilitates efficiency assessment by allowing peer group comparisons and identifying efficient and inefficient units within a specific context. Additionally, it facilitates benchmarking, where efficient units serve as role models for others, guiding best practices and resource allocation. Lastly, the CRS model considers sensitivity to input proportions, although this assumption of proportionality may not hold in scenarios with varying input mixes.

Variable Returns to Scale (VRS) Model:

The VRS model relaxes the assumption of constant returns to scale, allowing for variations in efficiency due to different scaling factors (Banker et al., 1984). This model offers flexibility in scaling, accommodating nonlinear input-output relationships and providing a more realistic assessment of efficiency. Additionally, VRS facilitates the customisation of efficiency frontiers, where each Decision-Making Unit (DMU) seeks an optimal weight bundle to maximise its CRS-efficiency score under VRS. Furthermore, it has the ability to handle extreme cases in heterogeneous environments where units operate at different scales.

Inputs Orientation

The paper discusses using an input-oriented DEA framework to analyse HN efficiency. It highlights the growing demand for health services, which requires accurate estimation. The approach is more appropriate for this context because it focuses on optimising resource use to meet uncertain demand (Ozcan, 2014).

The mathematical formulas for CRS and VRS with orientation towards inputs in DEA can be expressed as follows, using DEAP version 4.1 (DEAP) (T. Coelli, 1996; T. J. Coelli, 1995; Cooper et al., 2011b; Ozcan, 2014):

1. CRS Model with Orientation Input (Charnes et al., 1978; T. Coelli, 1996):

Efficiency Score (CRS) = ∑k=1mjk-yik / ∑j=1nkj-xij

Where:

- xij represents the amount of input / used by Decision Making Unit (DMU) j.
- yik represents the amount of output k produced by DMU j.

- xj and yik are the weights assigned to inputs and outputs, respectively, obtained from the DEA optimisation process.

2. VRS Model with Orientation Input (Charnes et al., 1978; T. Coelli, 1996):

Efficiency Score (VRS) = ∑k=1mjk-yik / ∑j=1nkj-xij

Where:

- xij represents the amount of input / used by Decision Making Unit (DMU) j.
- yik represents the amount of output k produced by DMU j.
- xj and yik are the weights assigned to inputs and outputs, respectively, obtained from the DEA optimisation process.

These formulas represent the ratio of weighted sums of inputs to weighted sums of outputs for each DMU, indicating their relative efficiency in utilising inputs to generate outputs under the CRS and VRS assumptions.

CHATGPT

The process of calculating efficiency scores using GAI ChatGPT involves defining inputs and outputs for each unit or entity, normalizing data to ensure comparability, choosing a DEA model based on the data and research question, formulating the DEA linear programming problem, solving the linear programming problem using appropriate optimization techniques, and interpreting the results. Units with efficiency scores of 1 are considered efficient, while scores less than 1 indicate inefficiency. The DEA analysis provides efficiency scores for each unit, indicating how efficiently they utilize resources to generate outputs. The results are then analyzed to identify factors contributing to inefficiency and opportunities for improvement. GAI tools like ChatGPT can assist in various stages of this process, but the actual calculation of efficiency scores typically requires specialized software or programming tools designed for DEA analysis.

1.4. Second Stage Tobit model

Hoff explored that second-stage DEA often encounters Tobit regression, which assesses the relationship between exogenous factors (non-physical inputs) and DEA efficiency scores. It is, however, not obvious that Tobit is the only, or optimal, approach to modelling DEA scores (Haldrup, 1998; Hoff, 2007). In exploring the relationship between DEA efficiency scores and hospital characteristics, the aim is to uncover how various factors influence the efficiency (or inefficiency) of hospitals.

This analysis delves into understanding which specific attributes or variables contribute to better or worse performance according to DEA assessments. By employing the censored Tobit model, which accounts for the lower-bound censoring of the dependent variable at zero, this study aims to provide a comprehensive understanding of the determinants of hospital efficiency. Changing DEA scores to inefficiency scores also makes it easier to understand the results, pointing out the things that make hospital operations less efficient (Er-Rays, 2021b; Er-Rays & Att Lemgeddem, 2020a; Hoff, 2007; Linna & Häkkinen, 1999; Tobin, 1958; Zere, 2000). This approach facilitates actionable insights that can inform strategies for improving hospital performance and resource allocation in healthcare systems.

Inefficiency score = 1 / (DEA score - 1)

The model is structured as follows:

$y = \beta iXi + ui$

Where:

- yi represents the observed inefficiency score for hospital i.
- βi is a vector of unknown parameters with dimensions k×l.
- Xi is a vector of explanatory variables with dimensions ×1.
- ui follows a normal distribution with mean 0 and variance.

The observed inefficiency score yt takes on the value of the predicted inefficiency score yi∗ if yi∗ > 0, and 0 if yi∗ ≤ 0.

Thus, the empirical regression model can be expressed as:

$INEFF = \alpha 0 + \beta 1HOP + \beta 2DOC + \beta 3NURS + ei$

where:

- INEFF denotes the inefficiency score.
- α0 is the intercept.
- HOP, DOC and NURS represent the explanatory variables.
- e/ is the error term.

2. Results

2.1. Descriptive statistics for the study variables

This research included all Moroccan hospitals, with the exception of one for which the data are incomplete. The collected data covers the year 2022. Table 2 summarizes the descriptive statistics for input and output variables used in all HN. The dataset reveals significant variability in healthcare provision across different regions and hospitals in Morocco. The average hospital activity is 75,427, with a wide range from 1,362 to 634,016. The mean number of specialised consultations is 49,371, with a similar level of variability. The average activities of public hospital laboratories are 408,168, with a significant standard deviation of 831,227. The average number of surgical services is 4,030, with a range of 36 to 35,633. The dataset comprises four hospitals on average, with a standard deviation of 4, reflecting variability in the number of hospitals across provinces. The mean total number of doctors and nurses is 129 and 320, respectively, with considerable variability. The mean population per province is 518,992, with a wide range from 44,112 to 3,613,337. These descriptive statistics highlight the diversity and heterogeneity of healthcare provision across different regions and hospitals in Morocco. Further analysis, such as correlation or regression analysis, could explore relationships between these variables and identify factors influencing hospital performance and healthcare outcomes.

Table 2: Descriptive statistics of inputs and outputs variables (N = 12)

Statistical Measure	Hospital Activity	Specialised Consultations	Public Hospital Laboratory Activities	Surgical Services	Hospital	Doctors	Nurse	Population Each Region
Mean	446,277	284,9	2,512,151	2,512,15	28	916	2,101	3,095,079
Standard Error	92,226	66,14	625,770	625,77	5	243	451	648,113
Median	430,945	228,55	2,223,482	2,223,48	27	664	1,775	2,854,550
Standard Deviation	319,479	229,12	2,167,731	2,167,73	16	842	1,563	2,245,130
Minimum	23,203	18,42	98,901	98,90	3	58	242	194,066
Maximum	929,225	772,09	8,232,607	8,232,61	56	2,66	4,891	7,641,949
Sum	5,355,33	3,417,45	30,145,810	30,145,8	331	11	25,213	37,140,944

Source : authors

2.2. DEA : First Stage

Figure 1 presents the estimated CRS and VRS technical efficiency and scale efficiency for each HN. The average CRS technical efficiency score was 0.474, the VRS technical efficiency score was 0.644, and the scale efficiency was 0.745. Overall, 11 (92%) of the regions had a CRS technical efficiency score of less than 1, while the Labyoune-Sakia El Hamra HDR demonstrated the highest level of efficiency with a score of 1. On the other hand, 09 (75%) VRS were technically efficient with less than a score of 1, while Rabat-Salé-Kénitra, Labyoune-Sakia El Hamra, and Eddakhla-Oued Eddahab HDRs were efficient, and 25% of the HN had a technical efficiency score of 1. The majority of HN exhibited both models of technical efficiency scores, with 9 HN for CRS and 7 HN for VRS being less than 0.6.

The technical efficiency analysis using GAI ChatGPT revealed that the mean CRS efficiency across regions is approximately 0.730, while the mean VRS efficiency is about 0.581. Among the regions, Béni Mellal-Khénifra, Labyoune-Sakia El Hamra, and Eddakhla-Oued Eddahab attained maximum efficiency scores of 1 for both CRS and VRS models. This equates to 20% of the total regions achieving perfect efficiency. These findings highlight variations in efficiency levels across regions, with some demonstrating higher efficiency than others.

Significant disparities emerge when comparing technological efficiency between DEA Software and GAI ChatGPT. In terms of DEA software, the average CRS technical efficiency score for all regions was 0.474. This metric deemed only 92% of hospitals to be technically efficient. Conversely, the average VRS technical efficiency score stood at 0.644, with 75% of hospitals achieving technical efficiency. The Labyoune-Sakia El Hamra HDR stands out, with perfect efficiency scores of 1 for both CRS and VRS models, whereas other regions showed varying levels of efficiency. However, the analysis of the data using GAI ChatGPT revealed a slight increase in the mean CRS efficiency to approximately 0.6914, while the mean VRS efficiency was around 0.5461, indicating a 26.4% difference. This discrepancy suggests a 31% higher efficiency for CRS and a 17% lower efficiency for VRS compared to DEA Software. Furthermore, using this method, Béni Mellal-Khénifra, Labyoune-Sakia El Hamra, and Eddakhla-Oued Eddahab HDRs achieved flawless efficiency scores. These findings underscore the variability in efficiency levels among regions and the potential for different outcomes using diverse analytical methods.

2.3. Tobit regression: Second Stage

The study uses Tobit regression analysis the factors effect on inefficiency of HN (DEAP version 2.1) using STATA 18 software (Table 4). The model is statistically significant, indicating that at least one of the coefficients is non-zero. The model explains approximately 55% of the variation in inefficiency. The coefficients for hospital activity and nurse are statistically significant at 0.05, suggesting that an increase in hospital activity and nurse are associated with higher inefficiency. The coefficients for "doctors staff" and "population" are not statistically significant, indicating no significant relationship between these variables and inefficiency. The intercept (.cons) is -0.3519811, which is not statistically significant, indicating that there is no evidence for a non-zero inefficiency when all independent variables are zero (table 03).

The statistically significant coefficient for hospital activity suggests that this factor may be an important driver of inefficiency in the studied system. However, the non-significant coefficients for doctors, staff, and population suggest that these variables may not significantly impact inefficiency. The negative and significant coefficient for nursing staff implies that increasing the number of nursing staff may lead to a decrease in inefficiency, which could have implications for resource allocation and staffing decisions within healthcare facilities. The non-significant intercept suggests that there are likely other unobserved factors contributing to inefficiency in the system. This analysis sheds light on the factors driving inefficiency in the system under study, but additional research may be necessary to comprehend the intricate dynamics and enhance the accuracy of the model.

Table 3 : Tobit regression of VRS (DEAP software)

Variable	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
Hospital activity	0.0772036	0.0304739	2.53	0.035	0.0069308, 0.1474764
Doctors staff	0.0007434	0.0005524	1.35	0.215	-0.0005304, 0.0020171
Nurses staff	-0.0012601	0.0004183	-3.01	0.017	-0.0022247, -0.0002955
Population	2.84e-07	2.41e-07	1.18	0.274	-2.73e-07, 8.40e-07
Constant (.cons)	-0.3519811	0.3687832	-0.95	0.368	-1.202397, 0.4984344
/sigma	0.4406304	0.1053366	-	-	0.1977237, 0.6835371

| Number of obs = 12 | | LR chi2(4) = 16.46 | Prob > chi2 = 0.0025 | Log likelihood = -6.7323622 | Pseudo 0.5500

3 left-censored observations at inefficient ~ 1 < = 0 (9 uncensored observations and 0 right-censored observations).

Source: authors

The Tobit regression analysis the factors effect on inefficiency (GAI ChatGPT 3.5) (Table 4) provides valuable insights into the factors influencing inefficiency in the studied system. The model is highly statistically significant, explaining approximately 72.3% of the variation in inefficiency. The coefficients for doctors are not statistically significant, suggesting no significant relationship between this variable and inefficiency. However, an increase in hospital activity and nursing staff is associated with lower inefficiency, which is statistically significant at 0.05.

When all independent variables are zero, the intercept (.cons) is -0.732358 with a standard error of 0.5422317, indicating that there is no evidence to suggest a non-zero inefficiency. There are four left-censored observations, indicating that the model may not fully capture the range of inefficiency values present in the dataset. Like what the DEAP software model found, the statistically significant coefficients for hospital activity and nurses suggest that these factors may be a big reason why the system being studied isn't working as well as it could. The non-significant coefficients for doctors and population suggest that these variables may not significantly impact inefficiency in this context, possibly due to variations in the dataset or modelling techniques.

The negative and significant coefficient for nurses implies that increasing the number of nursing staff may lead to a decrease in inefficiency, consistent with the DEAP software and ChatGPT 3.5 model's findings. This analysis provides valuable insights into the factors influencing inefficiency in the studied system, with implications for healthcare management and resource allocation, as well as personal stuff. We need further research to validate the findings and address any limitations in the modelling approach.

Table 4: Tobit regression of VRS (ChatGPT 3.5)

Variable	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**
Hospital activity	0.1032411	0.0359893	2.87	0.021	0.0202496, 0.1862326
Doctors	0.0008436	0.0010562	0.80	0.448	-0.001592, 0.0032792
Nurses	-0.0028168	0.0009482	-2.97	0.018	-0.0050033, -0.0006303
Population	1.33e-06	2.82e-07	4.73	0.001	6.84e-07, 1.99e-06
Constant (_cons)	-0.732358	0.5422317	-1.35	0.214	-1.982747, 0.5180306
/sigma	0.4516999	0.1103767	-	-	0.1971708, 0.7062289

Source: authors

| Number of obs = 12 | LR chi2(4) = 28.64 | Prob > chi2 = 0.0000 | Log likelihood = -5.4861643 | Pseudo R2 = 0.7230 |

4 left-censored observations at inefficient ~ A < = 0 (8 uncensored observations and 0 right-censored observations).

3. Discussion

The study's findings show that the majority of HN within each HDR were more inefficient when using GAI ChatGPT compared to DEAP version 2.1. This difference between the two methods suggests: On the one hand, GAI ChatGPT 3.5 as a method to calculate technical efficiency provides valuable insights into technical efficiency for AI developers and managers. It can analyse vast amounts of data, providing data-driven insights that help identify areas for improvement. It can also handle complex technical efficiency problems, offering solutions based on a variety of factors. GAI provides real-time feedback on technical processes, enabling immediate adjustments. Managers and developers can adapt their approach to measuring efficiency by customising AI models to specific contexts. GAI solutions can scale effortlessly to handle large datasets and diverse technical processes, making them suitable for organisations of all sizes and complexities. AI-powered solutions enable more informed decision-making, leading to better resource allocation and performance optimisation. Overall, GAI ChatGPT 3.5, is a powerful tool for measuring technical efficiency in AI development, allowing organisations to streamline processes and achieve greater success.

On other hand, technical efficiency using DEAP 2.1 software, the results of this study align with previous research conducted in several African countries (Africa WHO, 2023; Arhin et al., 2023; Babalola et al., 2022; Ibrahim et al., 2019; M. Kirigia Joses, 2015; Musoke et al., 2023), which demonstrate the extensive occurrence of technological inefficiency. For example, in Morocco (Er-Rays & Alt-Lemgeddem, 2020; Er-Rays, 2021a; Er-Rays, Alt-Lemgeddem, et al., 2024; Er-Rays, M'dioud, & Alt-Lemgeddem, 2024; Er-Rays, M'dioud, Alt-Lemgeddem, et al., 2024; Er-Rays & Alt Lemgeddem, 2020b; Er-Rays & M'Dioud, 2024). For instance, studies in countries (see section 10 to day) like Morocco, Benin, Ethiopia, Burkina Faso, and Eritrea have highlighted challenges in productivity growth and technical efficiency among healthcare hospital.

For example, the study conducted by Asbu et al. in Benin found that only 43.5% of hospitals experienced productivity growth over a five-year period, indicating significant challenges in productivity management strategies (Asbu et al., 2003). Similarly, Ali et al.'s study in Eastern Ethiopia revealed that a majority of hospitals were technically inefficient, with decreasing efficiency trends over time (Asbu et al., 2003). The study of Kirigia et Asbu in Eritrea also underscored the importance of efficiency analyses in improving hospital performance, suggesting potential strategies for enhancing efficiency through resource allocation and optimisation. Marschall et Flessa showed that 14 health centres in rural Burkina Faso were relatively efficient, with DEA projections suggesting that inefficient units were too big to be efficient (Marschall & Flessa, 2009). Furthermore, studies in specific regions, such as Kwasbuk Natal province in South Africa and regional hospitals in Ghana, have identified factors that influence technical efficiency, such as catchment population, staff allocation, and expenditure patterns. These findings emphasise the need for tailored policy interventions to address inefficiencies and promote better healthcare delivery. Habib et Shahwan identified 17 hospitals as inefficient due to a decline in technical efficiency. Common factors affecting efficiency include software programme value, operational expenses, and employee number. The number of physicians also significantly impacts the hospital's financial efficiency. A sensitivity analysis was conducted for model validation (Habib & Shahwan, 2020). Kirigia et Asbu showed that the average constant returns to scale technical efficiency score was 90.3%, the variable returns to scale technical efficiency score was 96.9%, and average scale efficiency score was 93.3%. To make hospitals more efficient, the researchers could have increased outputs by 20,611 outpatient visits and 1,806 hospital discharges, or they could have transferred excess doctors, nurses, midwives, laboratory technicians, and beds to primary care facilities. The Tobit regression analysis revealed a negative sign for OPDIPD (outpatient visits as a proportion of inpatient days) and a positive sign for ALOS (average length of stay) (J. M. Kirigia & Asbu, 2013). Babalola et al showed that a significant proportion of the hospitals were technically inefficient. Factors influencing technical efficiency included catchment population, inpatient treatment per medical and nursing personnel, and expenditure per patient day equivalent. These findings highlight the need for improved efficiency in healthcare systems (Babalola et al., 2022). Lamessen et al. found that 80% of primary hospitals were pure technical efficient, while 46.67% were scale efficient for neonatal health services in three zones of Northwest Ethiopia. The mean pure technical and scale efficiency scores were 0.948 ± 0.113 and 0.887 ± 0.143, respectively. The study found that the total catchment population, incentive packages for clinical staff, and the educational status of the manager positively influenced the technical efficiency of hospitals (Lamessen et al., 2022).

Conclusion and recommendations

Enhancing the performance of Moroccan HN is vital to ensuring efficient healthcare delivery and optimal resource utilisation. Health manager makers in health directorate areas need precise data on the efficiency of hospitals' resource utilisation in order to make well-informed judgements. This study demonstrated the use of DEA techniques in each regional health directorate's HN. It used both the DEAP Version 2.1 software and the advanced GAI ChatGPT 3.5 to analyse efficiency differences among HN based on readily available data.

The study's findings offer empirical data on the technical efficiency of the sampled HN. Additionally, the findings emphasise the need for specific modifications in input and output factors in order to enhance the efficiency of hospitals that are currently inefficient. The comparison between DEAP V 2.1 and GAI ChatGPT 3.5 highlights disparities in their ability to recognise inefficiencies and the variables related to them.

The DEAP version 2.1 and ChatGPT 3.5 analyses identify the hospital activity (HOP) and the stuff nurse (NURS) as statistically significant in terms of inefficiency. This suggests that internal issues inside the hospital activity (HOP) and the stuff nurse (NURS) had a substantial impact on determining the levels of efficiency. We link the number of hospital activities (HOP) and the number of nurses (NURS) to reduced inefficiency, underscoring the significance of human resource management in improving hospital performance.

These conflicting findings underscore the importance of employing multiple analytical methods to gain a comprehensive understanding of HN effectiveness. Health policymakers and researchers can enhance their decision-making and improve healthcare delivery by leveraging both traditional DEA approaches and modern AI technology. This enables better-informed decisions and future research, as well as tailored interventions such as engaging with managers and healthcare staff, reducing regional health disparities, and enhancing the quality of care.

First, applying the principles of New Public Management (NPM) (Errami & Cargnello, 2016; Er-Rays et al., 2022b) to the public HN can be beneficial. This approach, based on contractualisation, accountability, and managerial practices, involves collaboration between the central administration, hospital directors, and managers of medical, paramedical, and administrative departments. These stakeholders would establish a contract to ensure alignment of goals and responsibilities.

Secondly, to reshape the relationship between healthcare institutions and citizens, particularly in nursing and medical services, adopting a Citisen Relationship Management (CIRM) strategy and embracing digital transformation in the health system is advisable. Moroccan hospitals could benefit from developing digital transition strategies (Er-Rays et al., 2022a), such as leveraging GAI ChatGPT with a focus on the national level. This would help harness collective awareness and sustain momentum through an ambitious and integrated health strategy.

Thirdly, optimising resource allocation, utilising GAI to improve healthcare accessibility for marginalised patients in remote areas, and analysing hospital performance at the regional level are essential steps in this process. Furthermore, these findings emphasise the dynamic nature of healthcare efficiency, highlighting the need for ongoing monitoring and adjustment to ensure continuous improvement in HN performance.

This study represented a relative research endeavour that can serve as a foundation for scholarly discussions regarding the merits and demerits of healthcare provision in hospitals. The primary challenge lies in reconciling organisational constraints, such as human resource management (including enhancing the productivity of medical services), waiting lists, and access to services, with patient preferences and the quality of healthcare. These observations emphasise the need for further research by expanding the list of input and output variables from an objectivist perspective. Therefore, it is imperative to explore several scientific research questions, such as: how to implement this model of care delivery in the field and develop GAI to enhance the performance of HNs in each HDR ?

Abbreviations

CRS: Constant Returns Scale, DEA: Data Envelopment Analysis, DEAP: Data Envelopment Analysis Programming, DMU: Decision Making Unit, ET: Technical Efficiency VRS: Variable Returns Scale, SDG: Sustainable Development Goals, HDR: Health directorate region, GAI: Generative Artificial Intelligence, HN: Hospital networks.

References

Africa WHO, W. H. O. R. O. for. (2023). Technical efficiency of health systems in the WHO African Region . World Health Organization. Regional Office for Africa. https://iris.who.int/handle/10665/371012

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6 (1), 21-37. https://doi.org/10.1016/0304-4076(77)90052-5

Ali, M., Debela, M., & Bamud, T. (2017). Technical efficiency of selected hospitals in Eastern Ethiopia. Health Economics Review, 7 (1), 24. https://doi.org/10.1186/s13561-017-0161-7

Arhin, K., Oteng-Abayie, E. F., & Novignon, J. (2023). Assessing the efficiency of health systems in achieving the universal health coverage goal: Evidence from Sub-Saharan Africa. Health Economics Review, 13 (1), 25. https://doi.org/10.1186/s13561-023-00433-y

Asbu, E. Z., Emrouznejad, A., Houmankan, A., Kirigia, J. M., Makoudode, P., Mensah, O. A., & Mwikisa, C. (2003). Technical Efficiency of Zone Hospitals in Benin. Afr. Health Monti. (Online) , 30-39. http://afrolib.afro.who.int/documents/2010/En/AHM12_30_39.pdf

Babalola, T. K., Qiugbele, H. O., Shahwan, M., & Moodley, I. (2022). Analysis of factors influencing technical efficiency of public district hospitals in KwaZulu-Natal province, South Africa. Human Resources for Health, 20 (1), 80. https://doi.org/10.1186/s12960-022-00777-2

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, 30 (9), 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2 (6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Coelli, T. (1996). A guide to DEAP version 2.1: A data envelopment (computer) program. Centre for Efficiency and Productivity Analysis University of New England, Armidale, NSW, Australia . https://scholar.google.com/scholar_lookup?&title=A%20Guide%20to%20DEAP%20Version%202.1%3A%20A%20Data%20Envelopment%20Analysis%20%28Computer%29%20Program&publication_yc

Coelli, T. J. (1995). Recent Developments in Frontier Modelling and Efficiency Measurement. Australian Journal of Agricultural Economics, 39 (3), 219-245. https://doi.org/10.1111/j.1467-8489.1995.tb00552.x

Constitution (2017). https://www.cg.gov.ma/fr/espace-telechargement/constitution

Cooper, W. W., Seiford, L. M., & Tone, K. (2000a). Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software . Springer US. https://doi.org/10.1007/b109347

Cooper, W. W., Seiford, L. M., & Tone, K. (Eds.). (2000b). Returns to Scale. In Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software (p. 115-150). Springer US. https://doi.org/10.1007/0-306-47541-3_5

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). The Basic CCR Model. In W. W. Cooper, L. M. Seiford, & K. Tone (Eds.), Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software (p. 21-39). Springer US. https://doi.org/10.1007/978-0-387-45283-8_2

Cooper, W. W., Seiford, L. M., & Zhu, J. (Eds.). (2004). Handbook on Data Envelopment Analysis (Vol. 71). Springer US. https://doi.org/10.1007/b105307

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011a). Data Envelopment Analysis: History, Models, and Interpretations. In W. W. Cooper, L. M. Seiford, & J. Zhu (Eds.), Handbook on Data Envelopment Analysis (p. 1-39). Springer US. https://doi.org/10.1007/978-1-4419-6151-8_1

Cooper, W. W., Seiford, L. M., & Zhu, J. (Eds.). (2011b). Handbook on Data Envelopment Analysis (Vol. 164). Springer US. https://doi.org/10.1007/978-1-4419-6151-8_1

En-Naaoui, A., Kalcer, M., Chaouki, W., Mimouni, M., & Aguezoul, A. (2024). Health management risks in developing countries : Case of a sterilization unit in a Moroccan public hospital. Perioperative Care and Operating Room Management, 35, 100382. https://doi.org/10.1016/j.pcomm.2024.100382

Er Rays, Y., & Alt-Lemgeddem, H. (2020). La performance des établissements des soins de santé de bases au Maroc et COVID-19 : Application d'Analyse d'Enveloppement des Données et l'Indice de Malmquist . https://doi.org/10.5281/zenodo.4097235

Errami, Y., & Cargnello, C. E. (2016). The pertinence of new public management in a developing country : The healthcare system in Morocco. Canadian Journal of Administrative Sciences / Revue Canadienne des Sciences de l'Administration, 35(2), 304-312. https://doi.org/10.1002/cjas.1417

Er-Rays, Y. (2021a). Data Envelopment Analysis and Malmquist Index application : Efficiency of primary health care in Morocco and Covid-19. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(5), 971-983. https://www.researchgate.net/profile/Youssef-Er-Rays-3/publication/357072059_Data_Envelopment_Analysis_and_Malmquist_Index_Application_Efficiency_of_Primary_Health_Care_in_Morocco_and_Covid-19/links/61babd6b4b318a6970e47479/Data-Envelopment-Analysis-and-Malmquist-Index-Application-Efficiency-of-Primary-Health-Care-in-Morocco-and-Covid-19.pdf

Er-Rays, Y. (2021b). Data Envelopment Analysis and Malmquist Index Application : Efficiency of Primary Health Care in Morocco and Covid-19. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(5), 971-983. https://www.researchgate.net/profile/Youssef-Er-Rays-3/publication/357072059_Data_Envelopment_Analysis_and_Malmquist_Index_Application_Efficiency_of_Primary_Health_Care_in_Morocco_and_Covid-

19/links/61babd6b4b318a6970e47479/Data-Envelopment-Analysis-and-Malmquist-Index-Application-Efficiency-of-Primary-Health-Care-in-Morocco-and-Covid-19.pdf

Er-Rays, Y., & Ait Lemgeddem, H. (2020a). Hospital performance in Morocco and COVID-19: Application of Data Envelopment Analysis and the Malmquist Index. International Journal of Accounting, Finance, Auditing, Management and Economics, 1(2), 334-352. https://doi.org/10.5281/zenodo.4027715

Er-Rays, Y., & Ait Lemgeddem, H. (2020b). La performance hospitalière au Maroc et COVID-19: Application d'Analyse d'Enveloppement des Données et l'indice de Malmquist. International Journal of Accounting, Finance, Auditing, Management and Economics, 1(2), 334-352. https://doi.org/10.5281/zenodo.4027715

Er-Rays, Y., Ait Lemgeddem, H., & Ezzahiri, M. (2024). Bibliometric Analysis of Global Research Trends on Digital Occupational Health Using Scopus Database. In M. Ezziyyani, J. Kacprzyk, & V. E. Balas (Eds.), International Conference on Advanced Intelligent Systems for Sustainable Development (AIZSD'2023) (p. 1-12). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-52388-5_1

Er-Rays, Y., & Ait Lemgeddem, H. (2021). Moroccan health system performance and COVID-19 between Bismarck and Beveridge model. 4(1). https://jiarims.org/volume-4-issue-1-html/

Er-Rays, Y., Ait Lemgeddem, H., & Ezzahiri, M. (2022a). La Transformation Numérique au Maroc à l'ère des variantes de Covid-19: Quelle approche? https://doi.org/10.5281/zenodo.6060806

Er-Rays, Y., Ait Lemgeddem, H., & Ezzahiri, M. (2022b). Le New Management Public à l'ère de Covid 19 et ses variantes : Quelle performance au Maroc? https://doi.org/10.5281/zenodo.6060764

Er-Rays, Y., & M'Dioud, M. (2024). Assessment of Technical Efficiency in the Moroccan Public Hospital Network : Using the DEA Method (p. 2024.02.22.24303214). medRxiv. https://doi.org/10.1101/2024.02.22.24303214

Er-Rays, Y., & M'dioud, M. (2024). ChatGPT in Healthcare Facilities : An Overview and Innovations in Technical Efficiency Analysis (SSRN Scholarly Paper 4771070). https://papers.ssrn.com/abstract.