Assessment of Public Health Performance in Relation to Hospital Energy Demand, Socio-Economic Efficiency and Quality of Services: An Italian Case Study

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Abstract. This study investigates the relationship between energy management and hospital performance in the Italian public healthcare network. Using data on energy consumption and hospital activity from 28 public Italian hospitals, we conducted a regression analysis to assess the impact of organizational efficiency and patient hospitalization propensity on energy costs. Our results show that an increase in organizational efficiency is associated with an increase in energy costs, while an increase in patient hospitalization propensity is also associated with an increase in energy costs. However, some hospitals showed a higher energy cost per capita than the average, indicating the need for better energy management practices. We suggest that better management of human resources could be more effective in reducing energy costs than purchasing new equipment and expanding structures. Additionally, we highlight the importance of developing guidelines for energy consumption management, prioritizing the acquisition of alternative or renewable energy, and designing, constructing, and managing hospital buildings with a focus on energy efficiency. These findings have important implications for policymakers and hospital administrators as they work to balance quality of care with economic efficiency.

Keywords: Public healthcare performance · Socio-economic efficiency · Territorial healthcare system planning

1 Introduction

Good health is essential to sustainable development, as established by the 2030 Agenda. Indeed, health has a central position in Sustainable Development Goal 3, which concerns "Good Health and Well-being." The goal also aims to achieve universal health coverage

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and provide access to safe and effective medicines and vaccines for all. It is closely linked to over a dozen targets in other goals related to urban health, equal access to treatments, and non-communicable diseases, among others. In fact, it represents a unique opportunity to promote public health through an integrated approach to public policies across different sectors. Specifically, Target 3.8 "Achieve Universal Health Coverage" aims to provide universal health coverage, including financial risk protection, access to quality essential health care services, and access to safe, effective, quality, and affordable essential medicines and vaccines for all.

Subsequent paragraphs, however, are indented. Despite this awareness underpinned by ambitious goals in recent decades, there has been a steady increase in the number of disasters, including pandemics, which have had significant impacts on societies and economies. The COVID-19 pandemic has shown that many countries around the world have been caught unprepared to deal with such a threat, and the safety net provided by the health infrastructure has failed even in the most developed countries, with considerable fallout and repercussions on the health sector in general. This has led to an increase in healthcare costs, with forecasts of a further upward trend, without an integrated system for monitoring the efficiency of the healthcare system in general and the quality of services in particular.

Therefore, the interest of academics, healthcare managers, and policymakers has increased in identifying measures to contain healthcare spending while ensuring service quality. In this context, various attempts have been made to improve provider efficiency, including activating competition between hospitals and the implementation of incentive-based payment systems. Proposed models aimed at maximizing public administration and social housing have demonstrated effectiveness in meeting public needs while ensuring fair compensation for private entities (Morano et al., 2021). Numerous studies have been conducted to assess hospital efficiency and its variation over time, in order to provide an accurate estimate of hospital productivity and costs, which can be used as a criterion for payment for hospital services and to improve national health provision. As a matter of fact in many countries, public policies concerning the reduction of beds and medical and nursing staff, hospital mergers and acquisitions, and lower investments in health infrastructure are now being reassessed. In addition, the decentralised organisation of the healthcare system is also being questioned, and in many cases, the re-centralisation of the system is being considered. Italy is one of the Western countries that has significantly reduced healthcare spending and decentralised management to the regional level. However, the effects of these policies are still being debated. Moreover, despite the changes in healthcare organisation, inequalities between regional systems have not decreased over the last 20 years. In the literature, there is still a broad consensus that these decentralisation plans, and the decentralisation process in general, have had an impact on increasing health inequalities not only between but also within regions.

Moreover nowadays, healthcare managers must consider the impact of exogenous economic factors, such as the progressive increase in the cost of energy resources throughout Europe, an increase that is even more relevant following the outbreak of the conflict in Ukraine and the inflationary spiral that is still in progress. According to the National Agency for Regional Health Services (AGENAS), funding of EUR 1.6

billion has been provided for the National Health Service entities for the year 2022 to counter the effects of the increase in the prices of energy sources.

Given this evidence, the assessment of the territorial health services usually crosses several dimensions to obtain a comprehensive composite indicator useful for classification and comparisons. Therefore the first contribution of the present work is to identify and measure the main latent variables that summarize the organizational components of public nosocomial facilities, as well as variables that can express patients' preferences for hospital choice based on best activity or outcome criteria. The second contribution of this paper presents a machine learning methodology using machine learning algorithms that can assist decision-makers in their choices. The third contribution explains the interaction between identified hospital components and per capita health expenditure on electricity through a linear regression model.

The paper is organized as follows: after introducing the problem and aims of the work, the next paragraph presents the methodological background and the case study to which it was applied. This is followed by a chapter with details of the study conducted, where most interesting results are presented and are then critically discussed in the following chapter along with an assessment of the proposed approach's innovativeness, potential, and limitations. The conclusions offer considerations of the methodology's implications for decision support at different scales and outlines possible follow-ups.

2 Background

In the literature, it has been observed that various demographic and economic factors play a role in the choice of healthcare facilities, such as income, propensity to travel, level of education, age, type of illness, need for frequent treatment, and trust and reputation of the facility and its operators.

The patient's decision-making process when considering the quality of services (real or perceived) can be divided into several stages, including information gathering, risk/benefit assessment, consultation with the physician, and choice of treatment. The patient experience is complex and depends on several factors, including satisfaction, quality of care, and effectiveness of the healthcare system (Wolf et al., 2021). The perceived quality of healthcare is related to the actual quality of care provided (Doyle et al., 2013). Patients' satisfaction with the healthcare system is influenced by their experience of care and their perception of adequate attention to their care needs (Bleich et al., 2009). Active patient involvement in treatment choice improves patient satisfaction (Shay & Lafata, 2015). From the perspective of hospital facilities, a significant factor for perceived quality is the facility's ability to effectively treat complex and specialized illnesses, i.e., the facility's specialization and the complexity of the clinical cases treated. Another essential aspect is the reputation of the doctors working there. These factors can be emphasized by marketing policies pursued (Falavigna & Ippoliti, 2013).

According to the literature, two main points of view need consideration when evaluating possible measures: social welfare and stakeholder theory. Hospitals should not only ensure high-quality medical services at reasonable costs to improve health in society, but also be concerned about the well-being of their customers and all other stakeholders involved in the process (Hajiagha et al., 2023).

Based on these assumptions, hospital management should be aware of all the variables that express the structure's human, financial, and technological resources, as well as the outcomes produced and the quality of life of patients. To obtain timely decisions by healthcare management with the aid of streamlined procedures and tools, methodologies based on Multi-Agent Simulation to support Decision-Making in healthcare infrastructures for the organizational management and actionable choices in health risk (Esposito et al., 2020), as well as methods based on Dynamic Network Visualization of space use to support spatial redesign related decisions to improve workflow effectiveness and patient well-being (Esposito & Abbattista, 2020), have been proposed.

Artificial intelligence-based approaches composed of optimization and machine learning (Mirmozaffari et al., 2022) have been conducted and applied in different fields and organizations to calculate, for example, public hospital efficiency (Hajiagha et al., 2023), rather than in the industrial and service sectors (Guede-Cid et al., 2021).

As such methodologies involve large volumes of data, they require data mining techniques such as feature extraction, selection, and classification to derive meaningful information from the data. Feature selection is a technique used to reduce dimensionality to prune the feature space and, consequently, reduce computational cost and improve classification accuracy by means of Principal Component Analysis (Alomari et al., 2022).

To overcome the limitation of the dimensionality of the available data, this study proposes, by means of Principal Component Analysis (PCA), a reduction in the number of variables available in national databases and frequently used in the literature for measuring hospital efficiency. The PCA will identify two distinct principal components, expressing respectively a summary of the hospital organization and an outcome of the propensity to hospitalize patients based on perceived quality. Furthermore, the relationship between hospital energy cost and the two identified components will be studied by applying a linear regression. The predictive values obtained for the 28 public hospitals will be discussed by applying an ANOVA analysis. The analyses performed in this study will be conducted in a machine learning environment.

This paper presents a case study of the Apulia region (Italy). The regional health system encompasses both public and private accredited facilities within a given region, forming an organized complex known as the regional health industry (Falavigna & Ippoliti, 2013). The Regional Health Service in Apulia is represented by six Aziende Sanitarie Locali (ASLs), as shown in Table 1. ASLs are public legal entities with autonomy in organizational, managerial, technical, administrative, patrimonial, and accounting matters, as well as entrepreneurial autonomy (in accordance with Article 3 of Legislative Decree No. 502 of 30 December 1992). ASLs are part of the National Health Service.

This study focuses on the regional public hospital network in Apulia, specifically analyzing 28 facilities as indicated in the National Health Service Data Bank of the Ministry of Health. The public network consists of 24 ASL Direct Hospitals, one Hospital Authority integrated with the National Health System (NHS), one Hospital Authority integrated with the University, and one Public Institute for Hospitalization and Scientific Care. Some facilities, as specified in the single hospital reorganization document approved by the Apulian Regional Council on 03/07/2019, have connected plexuses and/or hospitals located in different places from the main structure. Thus, for greater

accuracy in measuring the distance traveled by patients, all the physical plexuses indicated in the National Outcomes Plan have been considered. The total number of facilities considered for measuring the active mobility of Apulian patients is 37 (see Fig. 1), including admissions made by ASL and by territorial ambit, as indicated in the National Outcomes Plan.



Fig. 1. Division of regional territory into provinces and public hospitals in Apulia.

In terms of hospital classification in Apulia, there are 5 s-level hospitals, 12 first-level hospitals, 2 Scientific Hospitalization and Care Institutes (IRCCS), and 9 basic hospitals. The differences between these types of hospitals are described in the Ministry of Health's regulations on the definition of qualitative, structural, technological, and quantitative standards for hospital care, which are implemented under Article 1, paragraph 169, of Law no. 311 of 30 December 2004 and Article 15, paragraph 13, letter c) of Decree-Law no. 95 of 6 July 2012, converted with amendments by Law no. 135 of 7 August 2012. The hospital levels differ primarily based on catchment area, number of wards, and complexity.

3 Methodology

A literature review was conducted to identify variables commonly used in studies on hospital efficiency. The dataset used in this study was obtained from the National Health Service of the Ministry of Health and the National Outcomes Plan of the National Agency for Regional Health Services.

The variables considered for calculating hospital efficiency were: Human resources: Variables related to the number of doctors, nurses, and general hospital staff employed in the hospital; Capacity: Variables related to the hospital's capacity to receive and treat patients, including the number of beds and wards; Productivity: This variable refers to the number of patients treated and admitted to the hospital; Quality of care: This variable assesses the quality of care provided to patients through quality indicators, such as mortality, hospital readmissions, and surgical discharges; Patient length of stay: This variable refers to the length of time a patient stays in the hospital; Patient satisfaction: This variable assesses patients' satisfaction with the care they received in the hospital.

The 16 variables considered for the 28 public facilities in the Apulia Region were divided into two groups. The first group included variables related to the hospital's workforce and facility capacity, while the second group included the other variables. Table 1 presents the variables in each group. Note that variable Var_10 is a derived multiplicative indicator that measures intraregional active mobility and will be explained separately in Sect. 3.1.

Table 1. Organization variables of Apulia Public Hospital.

Organization variables	Definition	Reference No	Data sources
Var_1	No. of day hospital beds	Fang and Lahdelma (2016)	NHS Database
Var_2	No. of day surgery beds	Fang and Lahdelma (2016)	NHS Database
Var_3	No. of beds in ordinary hospitalization	Fang and Lahdelma (2016)	NHS Database
Var_4	No. of beds used	Fang and Lahdelma (2016)	NHS Database
Var_5	No. of departments used	Briestensky and Kljucnikov (2021)	NHS Database
Var_6	Total no. of physicians	Fang and Lahdelma (2016)	NHS Database
Var_7	Total no. of nurses	Fang and Lahdelma (2016)	NHS Database
Var_8	Total no. of hospital staff	Fang and Lahdelma (2016)	NHS Database

In the second group, we have included outcome variables that express the hospital's performance in terms of services provided and outcomes produced, rather than active mobility and thus the attractiveness of the facility (Table 2). The combination of these factors will contribute to the overall perceived quality of care by patients.

The methodology proposed in this paper involves a first phase of applying Principal Component Analysis (PCA) to the initial dataset. The dataset will be reduced in size by applying two distinct PCAs to the two groups of variables identified. The Principal Component for the first group will express Hospital Organisation, while the Principal Component for the second group will express Patient Admission Propensity.

The effects of climate change, along with the recent energy crisis, have brought energy efficiency issues in hospitals and the increased demand for more research on energy efficiency in buildings into the spotlight (Psillaki et al., 2023). Therefore, we included an additional study variable: the per capita cost of medical electricity per Apulian resident in relation to the number of physicians in the year 2020. This variable was calculated as the ratio of the resident population of the Apulia Region in the year 2020 divided by the number of physicians in each hospital (Gutierrez-Romero et al.,

Table 2. Outcome variables of Apulia Public Hospital.

Outcome variables	Definition	Reference No	Data sources
Var_9	No. of hospitalizations	Fang and Lahdelma (2016)	NHS Database
Var_10	Intra-regional mobility active by territorial scope	Colombi et al. (2017)	National Outcomes Plan
Var_11	No. of deaths at 30 days after hospitalization	Bleich et al. (2009)	National Outcomes Plan
Var_12	No. of interventions according	Fang and Lahdelma (2016)	National Outcomes Plan
Var_13	No. of hospital readmissions at 30 days after hospital discharge	Personal communication	National Outcomes Plan
Var_14	No. of inpatient days	Fang and Lahdelma (2016)	NHS Database
Var_15	No. of available days indicated	Fang and Lahdelma (2016)	NHS Database
Var_16	No. of surgical discharges	Personal communication	NHS Database

2021), multiplied by the value of the per capita health expenditure related to the energy costs of Apulia in the same year (AGENAS).

The methodological workflow, shown in Fig. 2, is a graphical representation of the complex analyses applied in this study using data analysis and machine learning tools, via the widgets available in the Orange software.

We chose to use the Orange software for our analyses because it represents a robust data mining tool (Mirmozaffari et al., 2022).

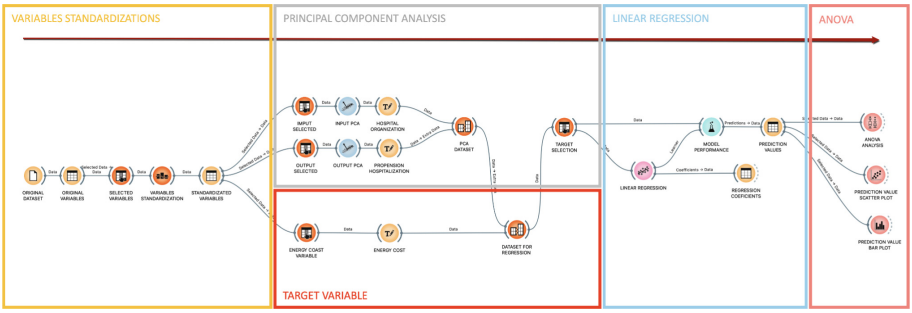

Fig. 2. Methodological workflow implemented in Orange. (Color figure online)

The new dataset, which includes the two identified principal components and the value of energy expenditure per capita of the population distributed by doctor, will be

subjected to training and testing by means of 10-fold cross validation. Linear regression will be used for this process. The learning algorithm (regressor) will process the input dataset and produce as output a prediction model capable of identifying the value of healthcare energy expenditure for given values of hospital organization and propensity to hospitalization of patients.

3.1 Intra-regional Mobility Active by Territorial Scope

In Italy, the Italian National Health Service has delegated management, economic, financial, administrative, organizational, managerial, etc. independence to the regions, while citizens are free to choose where to seek treatment throughout the country. While freedom of choice in seeking treatment can be considered an opportunity as well as a citizen's right, which must be protected (Nante et al., 2021), it is evident that the right to access and enjoy proximity to quality and affordable levels of care is equally important. In fact, mobility is not only due to preferences for specialized care but is often forced by gaps in local supply, such as a lack of beds or waiting time. Hence, strong territorial disparities in the supply of healthcare services can cause social injustices that must be equalized, hopefully upwards. In this sense, mobility for care is a crucial proxy index for measuring the state of the national public health service supply and for supporting healthcare policy design and hospital management.

The phenomenon of interregional migration flows of patients for care has been widely documented in the literature (Balia et al., 2018). Obvious discrepancies between the north and south of the country have been noted, and the consequences of the pattern of reimbursement for extra-regional care generate a financial flow in favor of wealthier regions, exacerbating the North-South divide in the National Health Service (Berta et al., 2021). A finer analysis of patients' travel patterns on a regional scale is necessary to identify the determinants of travel and to assess hospital attraction areas (i.e. catchment areas) that are linked to the services offered by individual hospitals that are part of each regional care network.

This is crucial to offer regional decision-makers and individual hospital managers benchmarks for evaluating the efficiency of the internal system and of each facility that is part of it. This allows for the more immediate identification of the causes of weakness in the system, such as poor quality supply or quantitatively insufficient availability compared to demand, on which to intervene with decisions at various scales. Similarly, it is useful for the recognition of hidden excellence to support decisions aimed at reproducing and disseminating the best practices already available in the regional health system and often unknown and undervalued.

In the present study, a patient's decision to seek treatment where they perceive better quality, subject to their economic availability and the medical offer proposed, is considered. 'Positive mobility' is defined as the flow of 'immigrants,' residents in the Apulia Region in 2020, who reach a hospital located in a different ASL from the one where the patient is a resident. Only intra-regional movements, i.e., within the region, made by patients resident in the region, have been evaluated. Therefore, admissions of non-resident patients are not considered. Since it is an evaluation of a closed system, only active mobility was taken into account since the difference with passive mobility would have produced no difference.

To calculate intra-regional active mobility in kilometers, we first calculated the interpolated distance between the capital city of the ASL where the patient resides and the city where the hospital providing the service is located (Dist kmHospi) (Falavigna & Ippoliti, 2013). Subsequently, we added the total active hospitalizations by ASL (HospiASL) and by territorial area (HospiArea), respectively, for each hospital. Finally, we calculated the intra-regional active mobility in kilometers by applying the following formula:

$$\text{Var_10} = \textit{Active mobility}_{\textit{infra regional}} = (\textit{Hospi}_{ASL} + \textit{Hospi}_{Area}) * \textit{Dist km}_{Hospi}$$

The movement made by the patient to a different territory from that of residence is considered to be due to a better perception of the quality of the service received. Although the displacement has been calculated by convention, along a hypothetical straight line, it would be interesting to measure the actual route that the "health client" would have to face to reach the hospital providing better "quality", while also analyzing other socio-economic factors that contribute to this choice.

3.2 Principal Component Analysis

Principal Component Analysis (PCA) is a machine learning technique that reduces the complexity of a dataset by transforming a set of original variables into a new set of linearly independent variables, called principal components. This method simplifies the representation of the data while retaining the most important information.

By reducing the size of the original variables, it is optimized while preserving as much information as possible. The transformation of the data takes place in a new coordinate system, where the new variables are orthogonal and arranged in order of importance (Hastie et al., 2009). PCA was used as a pre-processing phase of the data in a machine learning environment. We used Orange's select column widgets to split the initial dataset into the two groups of Input Variables (Table 1) and Output Variables (Table 2). We then linked the two groups to the PCA widgets, as illustrated in Fig. 3.

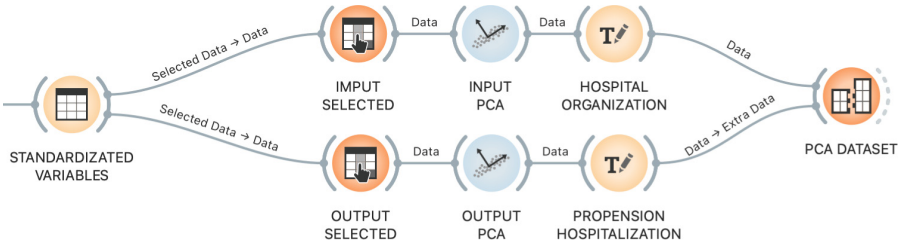

Fig. 3. PCA workflow.

Applying PCA to the first group of identified variables (Table 1), we obtained a principal component (Input_PC1) preserving almost 90% of the total variance with minimal loss of information. The graphical representation is shown in Fig. 4.

Applying PCA to the second group of identified variables (Table 2), one main components (Output_PC1) was identified, preserving almost 93% of the total variance. The graphical representation is illustrated in Fig. 4.

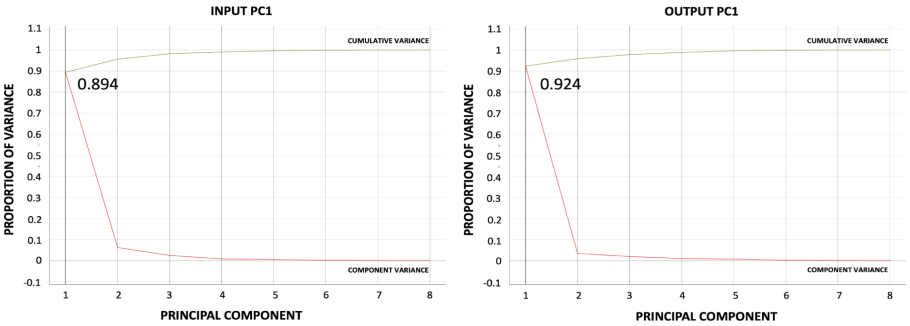

Fig. 4. Input PC1 and Output PC1 variance representation.

The incidence of the individual original variables on the main components can be visualised by means of the data table widget. The results produced and represented in Fig. 5 for the first principal component show a distribution in terms of incidence, which is fairly homogeneous across all variables and therefore PC_1 was renamed Hospital Organisation.

Data instances: 1
Features: 8
Meta attributes: 2

	components	variance	VAR_1	VAR_2	VAR_3	VAR_4	VAR_5	VAR_6	VAR_7	VAR_8
1	PC1	0.894017	0.331244	0.290424	0.368028	0.361608	0.367425	0.369782	0.369161	0.362916

Fig. 5. Incidence of Input variables on Input PC1.

The main output component was renamed Hospitalisation Propensity. The results are illustrated in Fig. 6.

Data instances: 1
Features: 8
Meta attributes: 2

	components	variance	VAR_9	VAR_10	VAR_11	VAR_12	VAR_13	VAR_14	VAR_15	VAR_16
1	PC1	0.923857	0.365744	0.338618	0.33546	0.3532	0.349674	0.364054	0.359203	0.36118

Fig. 6. Incidence of Output variables on Output PC1.

3.3 Machine Learning Algorithm

Linear regression is a statistical model that attempts to establish a linear relationship between a dependent variable (target) and one or more independent variables (features) (Fang & Lahdelma, 2016).

The linear regression model produces a linear function that attempts to predict the value of the dependent variable based on the values of the independent variables.

The model in multiple linear regression consists of more than one predictor variable:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_P X_P + \varepsilon$$

where Y is the response variable, $X_1; X_2; \ldots X_P$ is the predictor variables with p as the number of variables, $\beta_0; \beta_1; \beta_2 \cdots \beta_P$ are the regression coefficients, and ε is an error to account for the discrepancy between predicted data and the observed data (Fumo & Rafe Biswas, 2015).

3.4 Target Variable

Sustainability issues have become fundamental in all their various environmental, social and economic facets. One of the main challenges to be overcome by hospitals in this regard is energy management, based on environmental sustainability, which is used as a strategic means to achieve competitiveness and focuses on energy efficiency that includes policies, strategies and technologies designed to reduce energy consumption, pollutant gas emissions and costs (Borges de Oliveira et al., 2021).

Therefore, efficient energy management in hospitals has the potential to improve energy efficiency on the one hand and better management of public expenditure on health energy on the other.

Based on this assumption, in this study the per capita expenditure of the Apulian population in the calendar year 2020, distributed by hospital doctors, was identified as the target variable.

To calculate the cost of energy, we first calculated the ratio between the resident population in Apulia in 2020 ($Tot_{Res_{ASL}}$) and the total number of doctors in both public and private accredited hospitals, for each ASL ($Tot_{Doctors_{ASL}}$).

We then multiplied this ratio by the number of doctors in each public hospital, weighted by ASL ($Doctors_{Hospi}$) The resulting value for each facility, which is an expression of the population catchment area, was then multiplied by the per capita health energy cost of € 21.45 for the Apulian population in the year 2020, as indicated by the National Agency for Regional Health Services (AGENAS).

$$Energy\ cost = \left(\frac{Tot_{Res_{ASL}}}{Tot_{Doctors_{ASL}}} \right) * Doctors_{Hospi} * 21.45$$

4 Results and Discussion

It describes the second phase of the study, in which the target variable is "Per-capita energy cost" and the features are "Hospital Organisation" and "Hospital Propensity".

The Linear regression widget is used to provide the prediction algorithm with the dataset containing the variables to be analysed, and the performance of the model is evaluated using the Test and scores widget with a cross-validation of 10 folds. The results of the evaluation are described in Fig. 7.

The linear regression model has an MSE of 0.06, an RMSE of 0.2 and an MAE of 0.19, which indicates that the mean prediction error is relatively low. Furthermore,

Sampling type: 10-fold Cross validation

Scores

Model	MSE	RMSE	MAE	R2
LINEAR REGRESSION	0.06876586014125485	0.26223245440115694	0.19946152373923498	0.9312341398587451

Fig. 7. Prediction models performances.

the R2 of 0.93 suggests that the model explains about 93% of the variance in the data, indicating a good level of fit.

The coefficients of the regression model for the 28 public hospitals in Apulia are described in Fig. 8.

Data instances: 3
Features: 1
Meta attributes: 1

	name	coef
1	intercept	2.41838e-16
2	HOSPITAL ORGANIZATION	0.170574
3	PROPENSION HOSPITALIZATION	0.19381

Fig. 8. Regression model coefficients.

The dataset resulting from the analysis model proposed in the study, with the relevant predictive values generated by the linear regression, for the 28 public hospital facilities in the Apulia Region, is shown in Fig. 9.

Data instances: 28
Features: 2
Meta attributes: 3
Target: Numeric variable 'ENERGY COST'

	ENERGY COST	STRUCTURE NAME	LINEAR REGRESSION	Fold	HOSPITAL ORGANIZATION 0.894017	PROPENSION HOSPITALIZATION 0.923857
1	-0.745769	OSPEDALE OSTUNI	-0.665551	1	-1.86611	-1.78255
2	-0.460426	OSPEDALE FRANCAVILLA FONTANA	-0.583272	1	-1.6726	-1.52833
3	-0.378578	OSPEDALE CIVILE MARTINA FRANCA	-0.371675	1	-1.25215	-0.805925
4	-0.469693	OSPEDALE DELLA MURGIA - PERINEI	-0.365568	2	-0.851991	-1.1361
5	0.100588	OSPEDALE BARLETTA - 'MONS. R. DIMICCOLI'	-0.103025	2	-0.304612	-0.268841
6	-0.424145	OSPEDALE SCORRANO	-0.30743	2	-1.25587	-0.508038
7	0.29843	OSPEDALE ANDRIA - 'L. BONOMO'	-0.116555	3	-0.483352	-0.117045
8	1.6364	AO UNIV. 'OO RR FOGGIA'	1.91123	3	5.22458	5.05528
9	-0.502842	OSPEDALE CASARANO	-0.408186	3	-1.16271	-1.01687
10	0.761344	OSPEDALE BARI 'SAN PAOLO'	0.626752	4	1.83688	1.67788
11	-0.417241	OSPEDALE BISCEGLIE	-0.6698	4	-1.46354	-2.06907
12	-0.600637	OSPEDALE SAN SEVERO - TERESA MASSELLI	-0.45893	4	-1.24921	-1.22612
13	-0.687382	OSPEDALE MONOPOLI	-0.484848	5	-1.23629	-1.48059
14	0.151812	OSPEDALE BARI "DI VENERE" - TRIGGIANO	0.23771	5	0.213875	1.13649
15	3.22886	AO UNIV. CONS. POLICLINICO BARI	3.73946	5	10.0078	8.73097
16	-0.813643	OSPEDALE PUTIGNANO	-0.66868	6	-1.52997	-1.94286
17	-0.843701	OSPEDALE MANFREDONIA	-0.811186	6	-1.84558	-2.34117
18	1.35276	OSPEDALE LECCE - 'V FAZZI' (SAN CESARIO)	1.89555	6	3.32307	5.42516
19	-0.523552	OSPEDALE GALATINA 'S. CATERINA NOVELLA'	-0.667666	7	-1.35007	-2.06443
20	-0.522171	OSPEDALE MANDURIA 'GIANNUZZI'	-0.633389	7	-1.5107	-1.79218
21	-0.322481	OSPEDALE CASTELLANETA	-0.546519	7	-1.22505	-1.59083
22	-0.832146	IRCCS 'SAVERIO DE BELLIS'	-0.702665	8	-1.9766	-1.90177
23	-0.638146	OSPEDALE COPERTINO	-0.60114	8	-1.70254	-1.5926
24	1.92981	PRESIDIO OSPEDALERO CENTRALE TARANTO	1.13679	8	3.11079	3.55219
25	1.40147	OSPEDALE BRINDISI 'PERRINO'	1.18844	9	3.20641	3.40553
26	-0.70165	OSPEDALE CERIGNOLA 'G.TATARELLA'	-0.493111	9	-1.08998	-1.65949
27	-0.560034	ISTITUTO TUMORI GIOVANNI PAOLO II	-0.454713	10	-1.25174	-1.30056
28	-0.417241	OSPEDALE GALLIPOLI 'SACRO CUORE DI GESU'	-0.265152	10	-0.642778	-0.858102

Fig. 9. Hospital component scores.

In particular, the coefficient of the variable ‘Company organisation’ is 0.17. This means that an increase of one unit in the variable ‘Company organisation’ is associated

with an increase of approximately 0.17 units in the target variable 'Per capita expenditure on health energy'. Thus, an increase in business organisation (e.g. greater efficiency or better resource management) is associated with an increase in per capita expenditure on health energy.

Similarly, the coefficient of the variable 'propensity to hospitalise' is 0.19. This means that an increase of one unit in the variable "Propensity to hospitalise" is associated with an increase of about 0.19 units in the target variable "Per capita expenditure on health care energy". Thus, an increase in the propensity to hospitalise (e.g. an increased need for hospital care) is associated with an increase in per capita expenditure on health care energy.

The model intercept represents the value of the target variable 'Per capita expenditure on health energy' when all other variables in the model are zero. In practice, the intercept represents a kind of "expenditure floor" that the model predicts even in the absence of changes in the other independent variables.

Hospitals in their business complexity and their economic, social and environmental importance are large consumers of energy due to the continuous operation involving the use of complex electronic equipment to support clinical procedures.

A better management of healthcare resources in terms of a greater workforce, i.e. more hospital staff, rather than an increase in instrumental resources, beds and/or expansion of wards, which would contribute to an increase of an overall unit of the hospital corporate organisation, implies an increase in per capita healthcare expenditure on energy of 17%. From a managerial point of view, an assessment for a potential investment in corporate organisation would imply the same percentage increase for the energy cost item.

Analysing, at the same time, the hospital outcome factor counterbalancing the economic one, it can be seen that the relationship between the propensity to hospitalise patients and the relative increase in energy costs is quite robust. The final health outcomes understood as the reduction of discomfort, the prolongation of life, the decrease in the incidence of disease, rather than the satisfaction of users, family members, and the general population with the perceived overall quality and various aspects of care, are translated into the propensity to hospitalise patients. A propensity that is an expression of a need for care that sees its own unit increase associated with a 19% increase in the cost of energy.

A choice of resource allocation in the short/medium term can be optimised with the methodological approach proposed in this study, considering, on the one hand, the relationship between the hospital components and the cost of health care energy, but on the other taking note of the annual increase in the cost of health care energy per capita, which has increased in the three-year period 2020–2023, by about 142.65%, going to affect the regional health budget (AGENAS).

Observing the results of our linear regression analysis, represented graphically by means of the bar plot widget, by ASL and by hospital facility denomination (Fig. 10), it can be seen that the five regional public 2nd level facilities and two 1st level hospitals of ASL BA, have outliers with respect to the overall distribution of the regression values. These results are confirmed by the scatter plot (Fig. 11) distributing the predictive values by different type of level.

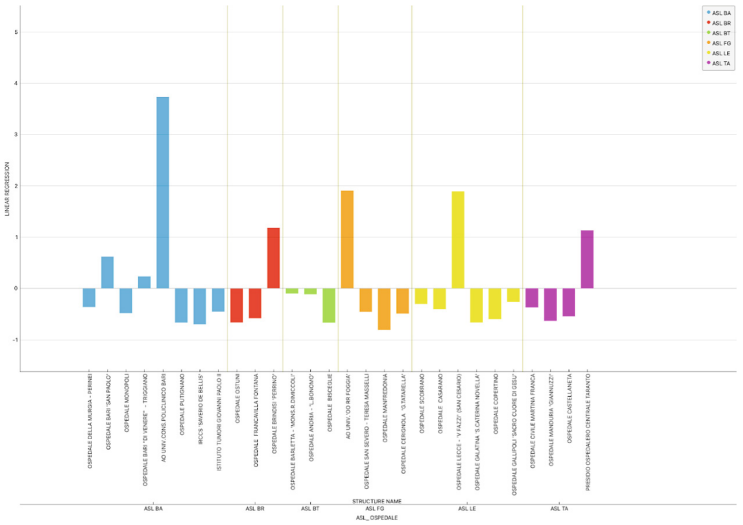

Fig. 10. Bar plot of linear regression predictive values.

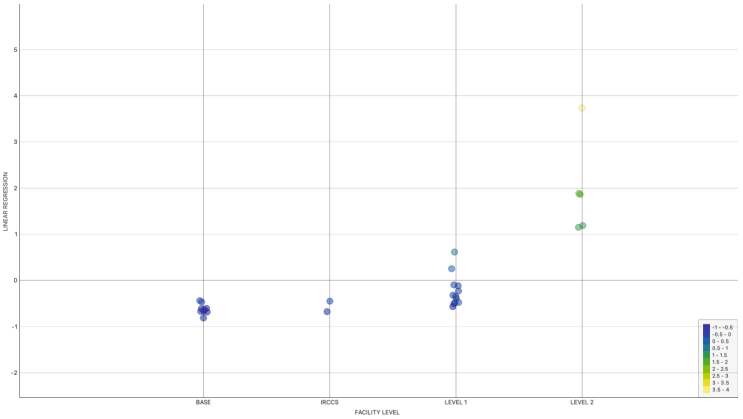

Fig. 11. Scatter plot of linear regression predictive values.

This assumption is confirmed by the ANOVA analysis applied to the same predictive regression values. With a p-value of < 0.005, the analysis confirms a significant difference between the different levels of the 28 public hospitals. As depicted in Fig. 12, there is a difference between the macro group consisting of basic, first level, and IRCCS hospitals compared to the second level hospitals.

The "LINEAR REGRESSION" column in Fig. 9 provides the estimated regression coefficients for each facility. For basic hospitals, IRCCSs, and level 1 hospitals, the estimated regression coefficients indicate that for a unit increase in hospital organization and patient admission propensity, there is an associated decrease in energy cost.

The opposite situation is verified for second level hospitals, in which an increase in hospital organization and an increase in the propensity to hospitalize will produce a higher energy cost.

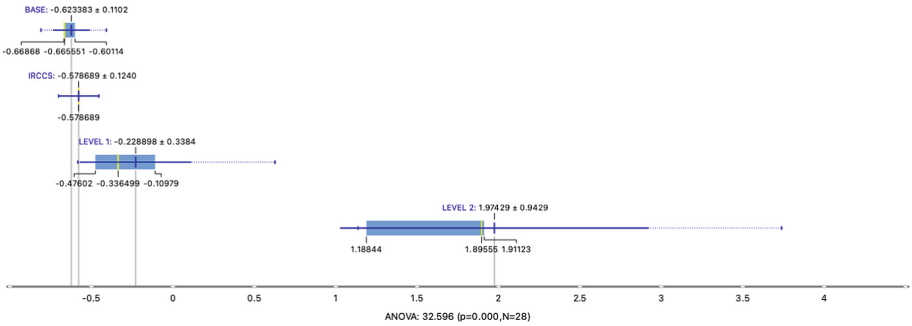

Fig. 12. Anova analysis applied to predictive regression values.

It is clear that there is no homogeneity in energy management practices among all hospitals. The management of healthcare companies should develop guidelines aimed at promoting a change in the organizational culture, by creating an energy consumption management plan following the ISO 50001 guidelines and prioritizing the acquisition of alternative or renewable energy. Additionally, they should focus on designing, constructing, and managing hospital buildings with a focus on energy efficiency and developing energy-related social responsibility programs (Borges de Oliveira et al., 2021).

The study found that an increase in organizational efficiency is associated with an increase in energy costs, while an increase in patient hospitalization rates is associated with an increase in energy costs. The analysis also highlighted some exceptions among hospital structures, with some showing a higher energy cost per capita than the average. The research suggests that better management of human resources could be more effective in reducing energy costs than purchasing new equipment or expanding structures. Furthermore, the study emphasized that energy costs have been increasing in recent years and that resource allocation choices must consider these rising costs.

Policies and decisions made by policymakers should aim to incentivize the public hospital network on the quality of services offered and not solely on economic productivity derived from DRGs, achieving a dual optimal allocation. An efficient allocation of economic resources that at the same time promotes an efficient redistribution of regional admissions offers optimal outcomes in terms of perceived quality.

5 Conclusion

There is no homogeneity in energy management among public hospitals, and better management of human resources could be more effective in reducing energy costs than purchasing new equipment and expanding structures.

The decision-makers, health professionals, and planners must understand, plan and specify the provision of medical care in terms of hospital capacity, availability, and supply.

The study proposes a future best practice for healthcare company decision-makers to have all the elements available, not only the company's own economic elements but also to take into account exogenous socio-economic factors. It also attempts to outline an integrated and unified vision to formulate coherent assessments of the entire regional hospital network in order to support the public decision-maker responsible for the regional healthcare system.

The study presented here has a limitation related to the calculation of the active mobility variable, as privacy legislation restricts access to the residence data of each patient, such as the exact address. For this reason, the route traveled by the patient to reach the hospital has been calculated as the straight line between the main city where the ASL is located and the municipality where the hospital is located. A planned follow-up is to integrate an analysis and representation system with a GIS to study hospital mobility with the actual distance traveled by patients, rather than relying on accessibility and variables related to the type and cost of transportation. This will provide a more accurate analysis of active healthcare mobility as an expression of the patient's choice of facility. Additionally, this approach will help to overcome the discrepancy between actual data availability for central hospitals that may combine several sites or connected hospitals that may be located in different and distant locations. Therefore, spatial variables relating to geographically dispersed facilities cannot currently be taken into account.

Regarding the usefulness of the proposed analysis tool, we propose developing what-if scenario analyses to simulate management decisions and resource allocation at the central regional level and at the local management level of individual hospital facilities, to verify the impacts and possible opportunities for improvement. This will involve an analysis by medical discipline, i.e., service offered, rather than using aggregate data. We also propose integrating the workflow proposed in this study with an analysis of DEA efficiency applied to hospital structures, using the main components identified as inputs and outputs.

Overall, the article suggests that policy-makers and healthcare organizations should aim to optimize the quality of services offered, not just the economic productivity derived from DRGs, in order to achieve an efficient allocation of economic resources and an efficient redistribution of regional admissions that offers optimal outcomes in terms of perceived quality.

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