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Modelling efficiency in primary healthcare using the DEA methodology: an empirical analysis in a healthcare district

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Abstract

Background Primary healthcare management efficiency conditions the functioning of specialized care and has a direct impact on the outcomes of the health system and its sustainability. The objective of this research is to develop models to evaluate the efficiency, including health outcomes, of the primary healthcare centres (PHC) of the Clínico – La Malvarrosa Health District in Valencia.

Methods To evaluate efficiency, Data Envelopment Analysis (DEA) was used with output orientation and variable returns to scale, with panel data from the years 2015 to 2019. In rates per 10,000 inhabitants, the inputs are: medical and nursing staff and pharmacy cost. The outputs are: number of consultations, hospital emergencies, referrals, avoidable hospitalisations, avoidable mortality and pharmaceutical prescription efficiency. As exogenous variables: the percentage of population over 65 years old, over 80 and case-mix. Three models were developed, all of them with the same inputs and different combinations of outputs related to: healthcare activity, outcomes, and both, in order to study the influence of the different approaches on efficiency. Each model is analysed both without exogenous variables and with each of them.

Results The efficiency results vary depending on the model used, although certain PHCs are always on, or very close to, the efficient frontier, while others are always inefficient. When healthcare activity outputs are considered, efficiency scores improve and the number of efficient PHCs increases. However, in general, the PHC score decreases throughout the evaluated period. This decrease is more pronounced when only activity outputs are included.

Conclusions DEA allows the inefficiencies of PHCs to be analysed and the efficient ones are clearly distinguished from the inefficient, although different efficiency scores are obtained depending on the model used. Evaluation can be according to healthcare activity, health outcomes or both, making it necessary to identify the expected objectives of the PHCs, as the perspective of the analysis influences the results.

Keywords Efficiency, Primary healthcare centres, Health outcomes, Data envelopment analysis

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Background

In 2000, an upward trend in health spending began, driven by the progressive ageing of the population, a growing demand for services by patients and the incorporation of highly advanced and increasingly expensive technologies. While the economy in general grew by 2.8% between 2000 and 2015, health spending increased by 4% [1], with no foreseeable changes in this trend for the coming years.

In 2020, health spending in developed countries approached 9.7% of GDP [2]. In Spain, at 122,800 million euros, it represented 10.7% of the GDP [3], below the European Union, at 10.9%. Health spending per capita in Spain, at 2,588 euros, remains very far from the European Union average, which stands at 3,159 euros [4].

The problem becomes greater when this growth in health spending is not accompanied by an improvement in health outcomes for the population [5]. In fact, one of the main threats facing the healthcare sector, especially in developing countries, is inefficient management in terms of optimizing resources [6].

Among the main objectives of the Spanish National Health System is the promotion of health in this environment of high healthcare expenditure and progressive increase [7], which makes it necessary to adopt containment measures to avoid a reduction in the quality of healthcare services [8].

Since the mid-1980s, a relatively powerful primary healthcare structure has been developed in Spain, which has always ranked well in international comparisons. However, in a process that has been going on for years, and caused by various factors, primary healthcare has presented problems, some of an acute nature, that have given rise to social concern [9]. In this sense, the recent pandemic caused by SARS-CoV-2 has revealed many of the weaknesses of both European and global healthcare systems, as well as the need to introduce changes in organizations and give primary healthcare the importance it deserves and that it has been losing [10–13]. In some European countries such as Spain, the United Kingdom and Portugal, the primary healthcare network constitutes a fundamental pillar that has supported the main virus containment measures [14].

Therefore, the evaluation of the efficiency of primary healthcare services is essential to detect the set of varied problems that affect the ability to offer high-quality services to the population, within the limitations of health spending. Furthermore, evaluation and analysis allows for better distribution and use of healthcare resources.

In this sense, frontier estimation methods that measure the inefficiency of an organization as the distance between a frontier generated by best practices and the actual performance of the units evaluated have been widely used in economic studies on productivity and technical efficiency in many areas: hospital costs, electrical energy, fishing and agriculture, manufacturing industry, public provision of transport or education services [15]. Their development has significantly advanced the practice of efficiency measurement in healthcare [16], although most studies focus on measuring the efficiency of healthcare and do not consider the results for care quality and the impact on the health of the population.

Within the frontier estimation methods for measuring the efficiency of service organizations, there are two groups: parametric models and non-parametric models. Both methodologies aim to evaluate production units using productivity indicators, which provide measurements that characterize the operations of the analysed units [17]. Every estimate using parametric functions has a defined mathematical form that is not always easy to identify [18]. The stochastic frontier is the most used parametric approach, as it assumes that it is not possible to completely specify the function, allowing the existence of error or random noise which is caused by exogenous factors outside the control of the managers [19].

Within the non-parametric models, one of the most used is data envelopment analysis (DEA), since it allows evaluation of the relative efficiency of decision making units (DMUs) by creating a production frontier using the best practice within the observed data.

One of the limitations of DEA methodology is that the number of efficiency-determining variables that can be introduced into the models depends on the number of DMUs considered in the analysis [20]. In order to avoid this dimensionality problem, when the ratio between the number of observations and the number of variables (inputs+outputs) is very small, as in our case, a panel data that includes data from several years is used. This approach groups together all cross sections, forming a single intertemporal data set that uses and treats separately all observations or DMUs from all the periods included in the analysis. In this way, each DMU is treated as if it were a different unit in each of the reference periods, which allows a unit in a specific period to compare its own performance for multiple years or periods, as well as with the performance of the other units, as well as to discriminate between efficient units, to provide greater robustness to the data, and to reduce the problem of studies with small samples [21, 22].

When using this approach, it is implicitly assumed that there are no substantial technological changes throughout the entire time period analysed, given all units within the panel are compared with each other. This may be questionable when long periods are to be analysed, but for our study, which is only 5 years, it is a perfectly acceptable hypothesis [21, 23].

In the review of the methodology of efficiency analyses with DEA, no standard approach is observed in the selection of input and output variables. In a systematic review from 2020, the main inputs were identified as: personnel costs, gross expenditure, referrals and days of hospitalization, as well as prescriptions and research; while the outputs included consultations or visits, registered patients, procedures, treatments and services, prescriptions and research [24]. Other authors distinguish between desirable and undesirable output variables, such as avoidable hospitalizations, which are variables to minimize [25, 26]. Furthermore, it is important to consider the existence of exogenous variables in the analysis [27, 28].

The development of information systems has allowed the use of real-world data from the PHCs of a health district of the Valencian Community, a region in the east of Spain, from which are drawn the output, input and exogenous variables that allow the development and comparison of useful models to measure the efficiency of the PHC.

The objective of this study is to develop models to measure the efficiency of the PHCs and to evaluate how the variables introduced in the models influence the efficiency scores, in order to design models that incorporate healthcare quality variables and healthcare outcomes as outputs, as well as developing a methodology that allows their evolution to be monitored.

Methods

The study period was from 2015 to 2019. The efficiency analysis includes the 18 PHCs of the Clínico – La Malvarrosa Health District in the Valencian Community, with an approximate covered population of 320,000 inhabitants.

The data are obtained from each of the patients with an assigned medical code as of January 1 for each year included in the study period, previously anonymized. This data is linked to a unique key per centre, used to generate a database in which records are grouped by PHC. The data used to draw up the variables was collected at an individual level and, subsequently, grouped by PHC, given the efficiency analysis is carried out at the PHC level. For grouping by PHC, the administrative grouping is followed. Each patient is assigned a Health Center by the health authority. This is included in the official health card.

The information sources used were: the Population Information System (SIP), the Hospital Minimum Data Set (MDS), the Patient Classification System (SCP-CV), mortality data (Mortality Registry of the General Directorate of Public Health), the centralized data of emergencies and referrals from Alumbra, the electronic outpatient clinical records (ABUCASIS) that encompasses the Ambulatory Information System (SIA), and the Pharmacy Prescriptions Manager (GAIA).

For efficiency analysis, traditional Data Envelopment Analysis (DEA) is used with panel data, output orientation and variable returns to scale (VRS), using the following expression:

$$max\varnothing\ + \epsilon$$

$$s.t.\sum\nolimits_{j=1}^{n}\lambda_{\,j}x_{ij} + s_i^{-x_{io}}\ i = 1,2\ldots.,m;$$

$$\sum\nolimits_{j=1}^{n}\lambda_{\,j}y_{rj} - s_r^{+\varnothing\,y_{r0}}\ r = 1,2\ldots.,s;$$

$$\lambda_{\,j} \geq\ 0\ j = 1,2,\ldots,n;$$

$$\sum\nolimits_{j=1}^{n}\lambda_{\,j} = 1$$

Given the characteristics of the Spanish health system, most of the inputs used by health organizations (personnel, equipment, etc.) are not easily controllable from primary health care centres. The use of output-oriented models is justified because the health sector must focus on obtaining the best health results, which is associated with greater technical efficiency [29].

One of the requirements of DEA methodology is that the DMUs analysed (in this study, the PHCs) must have a similar size to obtain more robust results [30]. Previous analyses have revealed the heterogeneity of the different PHCs in terms of covered population and, therefore, in terms of the level of healthcare activity and resources used. To remedy this drawback, the original data are transformed into rates per 10,000 inhabitants assigned to each PHC. These rates constitute the variables that were used in the models.

Among the variables available, we selected those that were identified in a previous study as producing the greatest power of discrimination or explanation of the variability. Other studies carried out in this field by other researchers were also considered [31–33].

The following are considered as variables indicating resources or inputs for each PHC: rate of doctors and nurses, and pharmacy costs. The medical and nursing staff is considered a non-discretionary variable, as the number of professionals in the centres are determined by the Regional Ministry of Health, and the directors of the PHCs have little room for manoeuvre.

As health outcome indicator variables for the outputs, which quantify the activity and quality of health care, the following healthcare activity indicators are included: rate of medical and nursing consultations, rate of referrals and rate of hospital emergencies; and for health outcomes: rate of avoidable hospitalisations, avoidable mortality and an efficiency indicator in pharmaceutical prescription.

Avoidable hospitalisations are obtained from the number of hospital admissions caused by pathologies that should be controlled from the PHCs and that represent a high percentage of the interactions of chronic patients with the healthcare system [34, 35]. The indicator of pharmaceutical prescription efficiency is measured through the prior development of other indicators, which consider whether, for a group of pathologies which represent a high percentage of total pharmaceutical expenditure, the most economical and effective drug has been correctly prescribed. This last indicator needs to be prepared in each centre.

Emergencies, avoidable hospitalisations and avoidable mortality are considered undesirable outputs. To introduce them into the program, it is necessary to identify them and carry out a prior transformation so that they are properly imputed in the analysis, especially when using output orientation, which tries to maximize the results for a given level of inputs. Therefore, the original values are replaced with modified values by subtracting a sufficiently high fixed amount (multiplying the result by -1 so that it has a positive value) [36–39]. By doing this, the traditional DEA model can be used, although it must be applied with VRS.

Finally, as exogenous variables, the ageing of the population attended by the PHCs is considered at two levels: the percentage of people aged 65 years or older and the percentage of people aged 80 years or older; and the morbidity of the population using case-mix. These are variables that are fixed exogenously and which PHCs cannot control, such as the characteristics of the population assigned to each centre in terms of age and burden of disease, and which determine the greater or lesser activity of the PHCs and the results they obtain, given that attending a younger and healthier population is not the same as serving one that is older and/or with greater morbidity.

The case-mix is obtained from the Clinical Risk Group (CRG) classification of the covered population of each PHC. Based on the CRG, a weight is assigned to each health status according to the clinical complexity of its treatment in economic terms [40]. In this way, the case-mix is a figure that indicates the burden of disease for patients in the different PHCs.

To treat these exogenous or non-controllable variables, we chose the approach proposed by Banker and Morey (1986) [41, 42], an alternative offered by practically all DEA specific software.

Previously, a correlation analysis was carried out between the variables to identify possible multicollinearity.

The DEA models were made with the interactive web application deaR, programmed in R [43].

Three models were developed which include the 18 PHCs in a panel of 90 observations, each model with four different specifications regarding the exogenous variables introduced (Table 1). All models took as inputs: pharmacy cost and the number of doctors and nurses. The variables related to personnel are considered non-discretionary inputs, given the rigidity of the Spanish public health system and the limited capacity that PHCs have to manage the number of doctors or nurses available to them.

Regarding the outputs, the first model was designed to evaluate the healthcare activity of the centres, with the rate of consultations, emergencies and referrals as variables. The rate of emergencies is treated as an undesirable output.

The second model evaluates the health outcomes of the population and uses the following as output variables: avoidable hospitalisations, avoidable mortality, and prescription efficiency. Avoidable hospitalisations and avoidable mortality are treated as undesirable outputs.

Table 1 Specifications of the models

Role	Model 1. Activity	Model 2. Outcomes	Model 3. Activity + outcomes
Inputs	PHC pharmacy cost (euros)*	PHC pharmacy cost (euros)*	PHC pharmacy cost (euros)*
	Doctors*	Doctors*	Doctors*
	Nurses*	Nurses*	Nurses*
Outputs	Consultations*	Avoidable hospitalisations*	Consultations*
	Hospital emergencies*	Avoidable mortality*	Hospital emergencies*
	Referrals*	Prescription efficiency (%)	Referrals*
			Avoidable hospitalisations*
			Avoidable mortality*
			Prescription efficiency (%)
Exogenous	Without exogenous	Without exogenous	Without exogenous
	% older than 65	% older than 65	% older than 65
	% older than 80	% older than 80	% older than 80
	Case-mix	Case-mix	Case-mix

*Rates per 10,000 inhabitants

In the third and final model, all the output variables are included, so that both the healthcare activity of the centres and the health outcomes are evaluated.

Furthermore, each of these models is carried out both with and without each of the exogenous variables of percentage of people older than 65 years, percentage of people older than 80 years, or case-mix as non-controllable inputs. Thus, a total of 12 different models are evaluated.

Results

Several models were evaluated with the objective of comparing them and selecting the one that most clearly differentiates the efficiency of the PHCs and that considers the outcomes for the health of the population, rather than the healthcare activity.

Our choice of the variables to include was based on previous analysis and on the review of the variables used in other studies, but also considered the limitations of the existing data collection process in the District, with the ultimate goal of obtaining a model that is useful for the best management of healthcare resources.

The correlation analysis between the variables shows high coefficients between the percentage of the population over 65 years of age and over 80 years of age, which are not simultaneously introduced into the models. There is also a high correlation between the case-mix and the pharmacy cost and the consultations rate. A greater morbidity or disease burden (case-mix) implies a greater consumption of medications and usually leads to a greater number of consultations. We included these variables in the analyses, as excluding them may lead to an incomplete representation of the activity carried out by the DMUs.

Table 2 Descriptive statistics for total sample observations

Role	Variable	Average	Standard deviation	Maximum	Minimum
Inputs	PHC pharmacy cost (euros)*	2,068,435	327,727	2,863,437	1,445,219
	Doctors*	7.3	0.9	9.7	5.8
	Nurses*	5.4	0.8	7.3	3.4
Outputs	Consultations*	65,110	9360	81,610	43,468
	Hospital emergencies*	3890	495	5143	2548
	Referrals*	3801	608	5549	2184
	Avoidable hospitalisations*	21.4	6.0	43.4	8.7
	Avoidable mortality*	16.1	5.2	31.2	5.6
	Prescription efficiency (%)	59.3	14.4	87.7	25.8
Exogenous	% older than 65	18.63%	2.57%	24.27%	13.76%
	% older than 80	5.58%	1.08%	8.41%	3.58%
	Case-mix	47.3	5.9	59.1	37.6

*Rates per 10,000 inhabitants

The descriptive statistical results of the entire sample, that is, 18 PHCs over a period of 5 years (2015–2019), making a total of 90 observations, reveal the existence of significant heterogeneity between PHCs, with very diverse sizes and large variations both in their resource allotment and in their outcomes (Table 2).

Figure 1 illustrates the evolution of all these variables throughout the 5-year period analysed. The graph shows a growing trend in personnel, as hiring took place in 2018 (more evident in the case of doctors), and in pharmacy costs, due to the increase in the prescription of medications and, in particular, the incorporation of increasingly expensive drugs.

Regarding the exogenous variables (or non-controllable inputs), no major variations are observed throughout these five years. These are the characteristics of the covered population in terms of population ageing and burden of disease, and it is usual that significant changes do not occur in such short periods of time.

Regarding the outputs, an upwards trend is observed in the rate of emergencies and referrals (represented by the scale on the right axis of the graph), while the rate of consultations (left axis) shows a clear drop, especially since 2018. This trend reflects a change in the way of recording some of the tasks that nursing staff usually perform, such as extractions, injectables, dressings, etc., and which are not strictly considered consultations and, in some centres, were not recorded. Since the end of 2018, none of these tasks have been recorded within this indicator, in order to reflect only and homogeneously nursing consultations. The drop in activity caused by this must be taken into account when analysing the results of the DEA models.

The evolution of the variables that measure health outcomes shows that large variations are not produced and the rates of avoidable hospitalisations and mortality are maintained at similar values over five years. Regarding pharmaceutical prescription efficiency, this presents a clear upward trend, indicating that an effort is being made by the centres to prescribe the most appropriate drugs at all times, for example, antibiotics or anti-inflammatories only when they are strictly necessary, or those active ingredients that are recommended in clinical guides for certain pathologies.

Table 3 summarizes the main descriptive statistics (average, standard deviation, maximum and minimum) of all the units evaluated in a dynamic context (90 observations), and for the different models analysed:

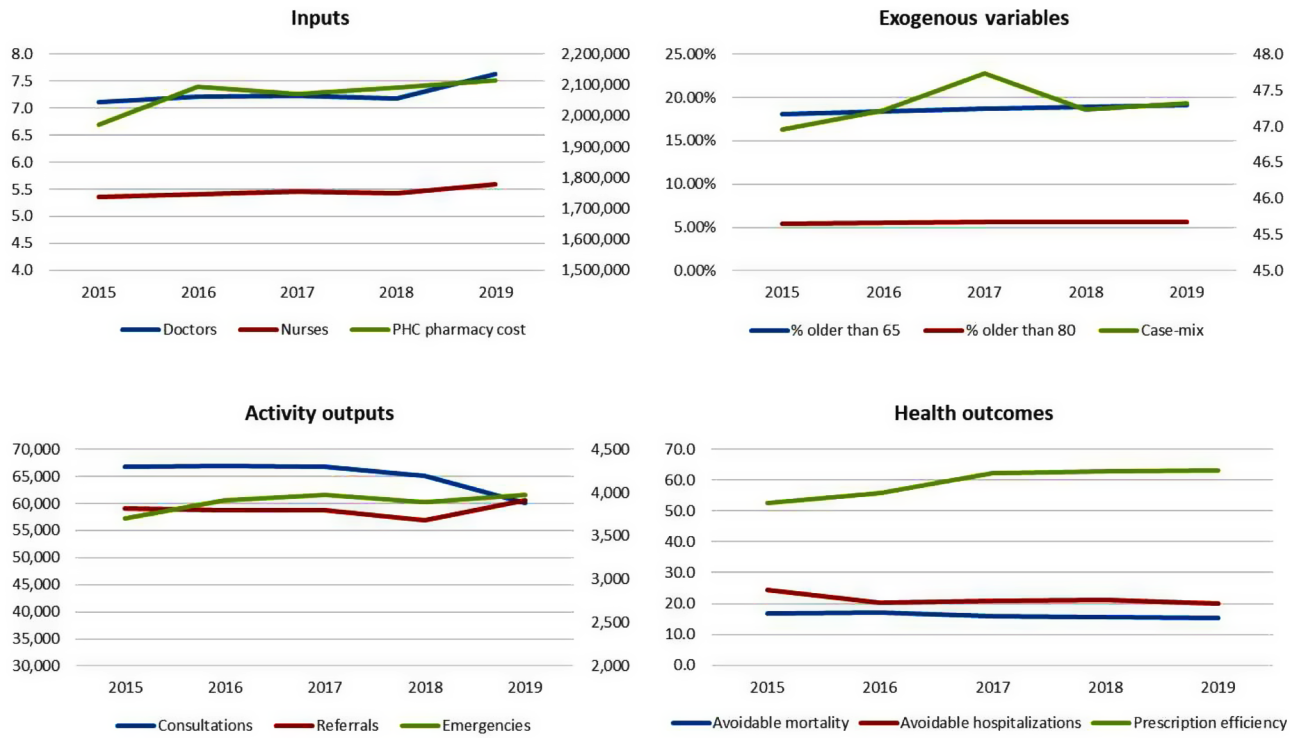

Fig. 1 Evolution of the average values over the period studied

Table 3 Descriptive statistics of the estimated efficiency scores for the different models

Model	Average scores	Standard deviation	Maximum	Minimum
1. Activity				
Without exogenous variable	0.9456	0.0548	1	0.7787
Including % older than 65	0.9780	0.0314	1	0.8645
Including % older than 80	0.9770	0.0312	1	0.8593
Including case-mix	0.9710	0.0400	1	0.8401
2. Outcomes				
Without exogenous variable	**0.8302**	0.1342	1	**0.4147**
Including % older than 65	0.8694	0.1341	1	0.4605
Including % older than 80	0.8710	0.1325	1	0.4541
Including case-mix	0.9451	0.0775	1	0.7266
3. Activity + outcomes				
Without exogenous variable	0.9808	0.0279	1	0.8757
Including % older than 65	0.9933	0.0152	1	**0.9168**
Including % older than 80	0.9923	0.0190	1	0.8952
Including case-mix	**0.9934**	0.0179	1	0.8919

activity, health outcomes and activity and health outcomes together, with output orientation, and both with and without including any non-controllable variable.

The average values of the estimated efficiency scores with the 3 models (activity, health outcomes and activity + health outcomes) differ considerably, being significantly lower in model 2, where the average value (0.8302) and the lowest minimum value (0.4147) are obtained when no exogenous variable is included. Furthermore, it is in model 2 where the greatest differences between the evaluated units are also observed, as can be verified when analysing the standard deviation.

When the variables that measure the activity of the centres (number of consultations, referrals and emergencies) are taken into account, the scores obtained are higher, and there is less dispersion between the units. This occurs in models 1 and 3, being much more evident in the latter. It is in model 3 where the average score is highest with case-mix (0.9934), and the highest minimum value is obtained (0.9168) when the percentage of population older than 65 is used.

This indicates that some of the PHCs analysed obtain better results when evaluating activity (model 1), while others obtain better results when health outcomes are included (model 2). When all the variables (model 3) are used together, some indicators are compensated by others and improve the global scores of the PHC.

One of the main objectives of this study is to analyse the efficiency of the PHCs in a dynamic context. Therefore, once the global results are analysed, Fig. 2 gives the temporal evolution of the average estimated efficiency scores for each of the 3 models and their different specifications throughout the 2015–2019 period.

It can be seen that scores follow a clearly downward trend over time, especially when activity indicators are used (models 1 and 3). It is in 2015 when the evaluated units obtain the highest scores and then descend, especially in 2016 and 2019. This trend lessens slightly when the non-controllable variables are incorporated into the models. In model 2 the trend is not so clear, but a slight descent is still observed from 2016. It must be taken into account that the variables used in this model imply few cases per year in each PHC (around 20 avoidable hospitalisations and 15 cases of avoidable mortality per 10,000 inhabitants) and therefore small variations in these indicators in each of the years can significantly affect the results. On the other hand, the downward evolution of the scores is influenced by an increase in the inputs or resources used (more personnel and higher pharmacy costs) and a decrease in outputs or results, especially in the number of consultations. Thus, the increase in the level of inputs and the reduction in the level of outputs jointly explain the decrease in the efficiency scores for these years.

Below, the scores of the different models are presented individually for each PHC. Table 4 shows the average score for the 5 years analysed for each PHC. A score of 1 (maximum value) is because the PHC obtained the maximum score in the 5 years and it is therefore considered to be totally efficient.

Significant differences can be seen between the results obtained from each of the models, and when some of the exogenous variables are incorporated, the scores improve in general.

In the first model, which evaluates activity, no PHC is efficient in all cases when exogenous variables are not taken into account. PHC14 and PHC18 are efficient when considering the age of the covered population, while PHC13 and PHC16 are totally efficient in the 5 years when case-mix is used. In model 2, where health outcomes are evaluated, it is observed that the scores obtained are lower in general, although PHC17, which was already among the most efficient units in model 1, is fully efficient in all years, both with and without exogenous variables, having a very low rate of avoidable hospitalisations and mortality, the best in the District, and an above average prescription efficiency indicator. All this means it achieves the best scores.

A notable case is PHC18, which has the highest rate of avoidable hospitalisations and avoidable mortality of the District, being considerably above the rest of PHCs. It can be seen it has one of the worst scores in the model without the exogenous variable, but once the burden of disease or age is considered, it becomes efficient.

Finally, in model 3, which evaluates activity and health outcomes together, the scores of all the PHCs improve. In this model, virtually all PHCs obtain very high scores close to 1, in all cases being greater than 0.9, and few differences between units can be observed. This indicates that the PHCs have a quite homogeneous performance when a more global analysis of their activity and outcomes is made. PHCs that obtained higher scores in model 1 compensate to some extent their poorer results in health outcome indicators, while the PHCs that are more efficient in health outcome indicators compensate for not scoring so highly in activity.

To sum up, there are PHCs that are more efficient when evaluating their activity, while others are more efficient

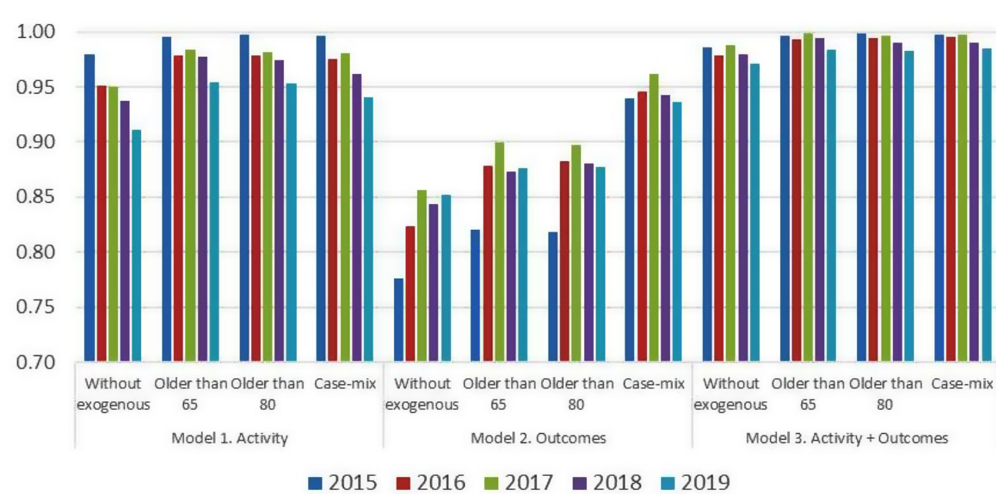

Fig. 2 Evolution of estimated efficiency scores by year

Table 4 Estimated efficiency scores for the 2015–2019 period for each of the PHCs

DMU	Model 1. Activity				Model 2. Outcomes				Model 3. Activity + outcomes			
	Without exogenous	% older than 65	% older than 80	Case-mix	Without exogenous	% older than 65	% older than 80	Case-mix	Without exogenous	% older than 65	% older than 80	Case-mix
PHC1	0.9833	0.9863	0.9860	0.9877	0.9239	**1**	0.9767	0.9294	0.9938	**1**	0.9974	0.9988
PHC2	0.9525	0.9557	0.9557	0.9565	0.7890	0.8068	0.8058	0.8557	0.9925	0.9939	0.9938	0.9946
PHC3	0.9272	0.9382	0.9490	0.9398	0.8484	0.8802	0.8981	0.9581	0.9644	0.9714	0.9783	0.9718
PHC4	0.9463	0.9568	0.9587	0.9988	0.7205	0.7351	**0.7301**	0.9659	0.9660	0.9795	0.9774	**1**
PHC5	0.9409	0.9510	0.9543	0.9472	0.8378	0.8595	0.8608	0.8865	0.9920	0.9930	0.9951	0.9920
PHC6	0.9884	0.9945	0.9994	0.9907	0.7903	0.8017	0.7962	**0.8239**	0.9916	0.9976	**1**	0.9937
PHC7	0.9866	0.9880	0.9880	0.9876	0.9817	0.9878	0.9858	0.9826	0.9916	0.9920	0.9919	0.9920
PHC8	0.9580	0.9655	0.9681	0.9636	0.8031	0.8289	0.8300	0.8894	0.9933	0.9961	0.9973	0.9958
PHC9	0.9411	0.9820	0.9581	0.9430	0.9980	0.9999	**1**	0.9995	**1**	**1**	**1**	**1**
PHC10	**0.8355**	0.9843	0.9929	**0.9230**	0.8789	0.9998	**1**	0.9861	0.9632	**1**	**1**	0.9960
PHC11	0.9264	0.9865	0.9507	0.9428	0.7343	0.7472	0.7412	0.8384	0.9357	0.9866	**0.9539**	**0.9566**
PHC12	0.8922	0.9955	0.9920	0.9869	0.9206	0.9482	0.9616	0.9850	0.9790	0.9991	0.9987	0.9993
PHC13	0.9930	0.9983	0.9950	**1**	0.9549	0.9807	0.9835	**1**	0.9966	0.9986	0.9972	**1**
PHC14	0.9815	**1**	**1**	0.9984	**0.6335**	**0.6676**	0.7342	0.9928	0.9943	**1**	**1**	**1**
PHC15	0.9149	**0.9277**	**0.9481**	0.9632	0.7436	0.7686	0.7483	0.9343	0.9675	**0.9711**	0.9812	0.9906
PHC16	0.9919	0.9936	0.9920	**1**	0.7246	0.7446	0.7490	0.9845	**1**	**1**	**1**	**1**
PHC17	**0.9941**	**1**	0.9975	0.9944	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
PHC18	0.8677	**1**	**1**	0.9538	0.6607	0.8921	0.8764	**1**	**0.9322**	**1**	**1**	**1**

when evaluating their health outcomes, and analysing the centres more globally, some aspects compensate for others and the PHCs present a more homogeneous behaviour and obtain good scores in all cases.

Finally, we examined the evolution of the PHCs individually. Table 5 shows the estimated efficiency scores for each PHC for each of the years 2015 to 2019. The average value of the 5 years is also included, which has already been commented on. Only the results of model 2 (outcomes) with output orientation and case-mix are presented, since this is considered the most relevant model, capable of detecting most differences between the PHCs, and which aims to maximize the outcomes in population health - the ultimate goal of the health system - and also takes into account the morbidity of the population served. In the event of the morbidity indicator not being available, it is be possible to replace it with the percentage of population older than 80, given the high correlation that exists between both variables. The results of the rest of the models are presented in the appendix.

In this model (see Table 5) significantly lower scores and more differences between the units are observed, although when using case-mix as a non-controllable variable, these differences are mitigated. When examining the evolution of some of the PHCs throughout the period studied, certain interesting aspects can be observed. Many of the PHCs obtain the highest score in 2015 and start to decline later.

In this case, 3 PHCs are efficient in all 5 years: PHC13, PHC17 and PHC18. Other PHCs such as PHC7, PHC9, PHC12, PHC14 and PHC16 are efficient in all years apart from one, which coincided with the years 2018 or 2019, when personnel were hired and, therefore, the level of inputs increased. In this model a downward trend of the efficiency score is not clearly appreciated, although units such as PHC5, PHC11 and PHC15 show a progressive worsening. The case of PHC6 is noteworthy, as it obtained the worst score in 2015, improved considerably in 2016 and 2017 and gave the lowest scores in 2018 and 2019. In addition, it is the PHC with the worst average score of the 5 years.

DEA methodology identifies the efficient PHCs as a whole. After carrying out the analysis, it can be observed that there is no clear combination of inputs and outputs that allows the units to obtain higher results. It is, however, evident that the results of each PHC are largely affected by the characteristics of their covered population. Nevertheless, it can be seen that certain PHCs are always efficient or remain close to the efficient frontier, while others are always inefficient.

The use of outputs that measure activity produces changes in the scores and increases the number of efficient PHCs. In addition, it can be seen that the PHCs underwent, in general, a clear decrease in their efficiency levels throughout the period evaluated. This decrease is more pronounced when only activity variables are included.

Discussion

This study analyses the efficiency of the 18 PHCs of the Valencia Clínico – La Malvarrosa Health District for a period of 5 years (2015–2019). This is the first efficiency evaluation of primary healthcare conducted in the Valencian Community. We used the technique of data envelopment analysis, a methodology widely used in previous studies in the healthcare sector [24, 31, 32, 44–46], to

Table 5 Evolution of efficiency scores for each PHC and year. Model 2, output orientation, case-mix

DMU	2015	2016	2017	2018	2019	Average
PHC1	0.8352	0.8797	0.9320	1	1	0.9294
PHC2	0.7909	0.8590	**0.8410**	0.8033	0,9844	0.8557
PHC3	1	0.9413	1	0.9703	0.8789	0.9581
PHC4	0.8736	0.9561	1	1	1	0.9659
PHC5	0.9528	0.9857	0.8289	0.8668	0.7983	0.8865
PHC6	**0.7479**	0.8905	0.9461	**0.7947**	**0.7404**	**0.8239**
PHC7	1	1	1	1	0.9128	0.9826
PHC8	0.8453	**0.7266**	0.9442	1	0.9311	0.8894
PHC9	1	1	1	0.9975	1	0.9995
PHC10	1	1	0.9784	0.9523	1	0.9861
PHC11	0.8615	0.9239	0.8433	0.7601	0.8031	0.8384
PHC12	1	0.9252	1	1	1	0.9850
PHC13	1	1	1	1	1	**1**
PHC14	1	1	1	1	0.9638	0.9928
PHC15	1	0.9359	1	0.8967	0.8390	0.9343
PHC16	1	1	1	0.9223	1	0.9845
PHC17	1	1	1	1	1	**1**
PHC18	1	1	1	1	1	**1**

estimate the efficiency scores of the PHCs with panel data [21, 23] and to compare the efficiency results obtained from three models with different specifications.

Data envelopment analysis, despite its limitations, is shown to be a useful methodology for the evaluation of the efficiency of PHCs and provides very valuable information for managers. It is of interest to compare the PHCs with best practices and determine possible improvements for those that are below that frontier, that is, the resources that should be reduced or the outcomes that must be improved.

Three models have been developed with different specifications to allow evaluation of PHC performing from different perspectives. Although the variables included in the models have a strong influence on the results, we observed that some PHCs are always efficient, or are very close to the efficient frontier, regardless of the model or the year analysed, while other PHCs are always inefficient or systematically obtain the lowest scores.

Those models that include variables for activity (models 1 and 3) and therefore carry out the analysis from a healthcare point of view, show a greater number of efficient units and the estimated efficiency scores achieved by the PHCs are higher, which implies that healthcare activity is taking place homogeneously in most units.

By incorporating variables for quality or healthcare outcomes (avoidable hospitalisations, avoidable mortality and prescription efficiency), more differences between centres are detected (especially in model 2). The introduction of only health outcomes as outputs assigns a lot of weight to these indicators and they discriminate more strongly in the evaluation of efficiency. Therefore, it is important to observe the evolution of the analysis over time to give greater consistency to the observed measurements. This demonstrates the importance of a suitable selection of the variables to be used, as evidenced in other studies carried out [24].

The inclusion of variables for characteristics of the covered population in terms of ageing and morbidity affects the efficiency results, making their incorporation in the analysis essential, as also demonstrated by other authors [25, 27]. It is also observed that the use of one or another of the exogenous or non-controllable variables (age or case-mix) does not substantially modify the results, which makes it easier to replace one variable with the other if one of them is not available.

The treatment of undesirable outputs is a complex issue and different alternative approaches can be found in the literature [25]. In this study, the simplest approach has been chosen, in which the original values are modified by subtracting a sufficiently high fixed amount (multiplying the result by -1 so that it has a positive value) [36–39]. This allows the use of the traditional DEA model, necessarily applying variable returns to scale.

The treatment of exogenous or uncontrollable variables is also complex as there are multiple methodological options, each with advantages and disadvantages. The simplest is that proposed by Banker and Morey (1986) [41], which is the one used in this work. It does, however, present important limitations, such as the influence on the results of the choice of constant or variable returns to scale, or requiring some restrictive assumptions such as the free availability and convexity of the achievable set, or the estimated efficiency scores may be systematically biased, increasing the potential production targets of inefficient DMUs [47]. The methodological option that is considered most appropriate by other authors is the non-parametric conditional model proposed by Daraio and Simar [48, 49]. This conditional efficiency model was used by Cordero et al. (2016), although its use is still scarce in the healthcare context [33]. Its main advantage is that it is not necessary to assume the assumption of separability and it allows the effect of exogenous variables to be incorporated directly into the calculation of efficiency scores, conditioning the production process to certain values of these variables. This option, although not used in this work due to its complexity, will be included in future research.

The number of variables that can be used in the models is limited, since to obtain reliable results it is recommended that the total inputs and outputs do not exceed one third of the PHCs analysed (in our case 18 PHCs) [50]. Once more, this implies a suitable selection of the variables and, in some cases, the prior use of other methodologies. To avoid this problem of dimensionality, as the complete information for the variables was available for the 5 years, panel data methodology was used, which also allowed us to analyse the evolution of efficiency in these units throughout the period. In this way, the results show that there has been a decrease in the efficiency levels of the PHCs over the period studied, especially when including variables for activity. When using variables that measure health outcomes, the worsening is not so evident, and it is possible to identify more differences between the PHCs.

Despite the limitations in the number of variables that can be included in the models, the introduction of correlated variables in the analysis is justified by the need to capture complete information on the performance of the DMUs [42]. By considering all the relevant dimensions, it is ensured that the DEA model reflects the complexity of the production process more precisely, and by reflecting the operational reality of the DMUs, they show that, in many practical situations, the input and output variables are naturally correlated due to the structure of the production process of the health care sector [41, 51]. Excluding correlated variables could lead to an incomplete or distorted representation of the performance of DMUs.

Furthermore, the introduction of correlated variables can improve the fit and accuracy of the DEA model by allowing better discrimination between DMUs. Although it increases the dimensionality of the model, it can also provide a more detailed and accurate assessment of performance [52]. Lastly, in many applied studies, the inclusion of correlated variables is not only common but necessary to capture all relevant dimensions of performance. Case studies in health, education and other sectors show how these variables contribute to a more complete evaluation [53].

There are still relatively few studies that evaluate efficiency in primary healthcare, especially in Spain. In most of them, the analysis is carried out from the point of view of the activity, given the impossibility on many occasions of accessing indicators that allow the evaluation of the quality of the care provided by the centres. However, not taking these quality indicators into account can end up rewarding, in some way, those centres that have greater activity than others, simply because they are operating with lower quality standards [54].

Likewise, incorporating other quality variables that are not usually available, such as user satisfaction surveys, or including as exogenous variables the deprivation index of the population assigned to each PHC [55], or other types of variables such as per capita income or education level [56], would allow different results to be obtained that more adequately reflect the real activity of the centres and the characteristics of their population. This would contribute to proposing more useful recommendations for the management of the PHC, which in turn would help to achieve a more efficient and higher quality health care. For this, it is also necessary to involve healthcare managers in the analysis, so that their preferences (and the goals they pursue) can be taken into account through the selection of the most appropriate input and output variables [57].

The efficiency scores found using this methodology only allows comparison within the set of PHCs considered. In this case, no major differences were observed in the scores obtained between the components of the group, especially with models 1 and 3, something that implies that healthcare activity is occurring homogeneously in the majority of units.

In order to establish a unified production frontier and thus achieve holistic comparability between regions within the field of efficiency evaluation, standardization and normalization of the variables used, including the exogenous, would be required, and a single DEA model would be applied for the evaluation. In this way, a meta-frontier of the set of DMUs could be obtained. These strategies would ensure that efficiency assessments are fair, accurate and sufficiently reflect the operating conditions for each region, enabling a valid and useful comparison between different regional contexts.

In this study, the traditional or radial DEA model has been used, which is the most common, although there are other methodological options with different perspectives, such as non-radial efficiency measures that include the Russell index, the additive models or the slack-based efficiency indicators [58], and which will be explored in future studies.

Conclusions

Data envelopment analysis is shown to be a valuable methodology to evaluate the efficiency of PHCs and is useful as a management tool in terms of resource allocation. It allows the inefficiencies of the PHC to be analysed, although it is necessary to identify the objectives of the centres, since the variables included in the models and the perspective of the analyses influence the results.

It is important that management focus its objectives on improving the health of the population (fewer emergencies, fewer avoidable hospitalisations, lower avoidable mortality) and incorporate variables for healthcare quality and health outcomes, and focus less on the activity (the number of consultations is not so important, but rather that they are necessary), as well as keeping in mind the characteristics of the covered population when performing the analysis.

It is essential to carry out this type of evaluation, since the identification of anomalies in efficiency behaviour can help in the management of primary healthcare centres and provide a better allocation of healthcare resources.

Abbreviations

CRG	Clinical Risk Groups
DEA	Data Envelopment Analysis
DMU	Decision making units
PHC	Primary Healthcare Center
VRS	Variable returns to scale

Supplementary Information

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Supplementary Material 1

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Author contributions

Conceptualization, D.V.-C. and I.B.-M.; methodology, D.V.-C. and I.B.-M.; software, S.G.-d.-J.; validation, D.V.-C. and I.B.-M.; formal analysis, S.G.-d.-J.; investigation, S.G.-d.-J.; resources, S.G.-d.-J.; data curation, I.B.-M.; writing—original draft preparation, S.G.-d.-J. and I.B.-M.; writing—review and editing, S.G.-d.-J. and I.B.-M.; supervision, D.V.-C.; project administration, I.B.-M. and

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Data availability
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Ethics approval and consent to participate
The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of HOSPITAL CLINICO UNIVERSITARIO DE VALENCIA (protocol code 2020/170 and date of approval 25 June 2020). Informed consent statement was deemed unnecessary according to national regulations, specifically according to the assessment of the Ethics Committee (CEIm) of HOSPITAL CLINICO UNIVERSITARIO DE VALENCIA, and in accordance with the Spanish Biomedical Research Law 14/2007 for observational studies. This study is retrospective and does not contain individual personal information, since the data were obtained from a secondary database with anonymized and dissociated information as stablished by the current legislation at the time of the study.

Consent for publication
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Competing interests
The authors declare no competing interests.

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