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Predicting healthcare expenditure by multimorbidity groups

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ABSTRACT

Objectives: This article has two main purposes. Firstly, to model the integrated healthcare expenditure for the entire population of a health district in Spain, according to multimorbidity, using Clinical Risk Groups (CRG). Secondly, to show how the predictive model is applied to the allocation of health budgets.
Methods: The database used contains the information of 156,811 inhabitants in a Valencian Community health district in 2013. The variables were: age, sex, CRG's main health statuses, severity level, and healthcare expenditure. The two-part models were used for predicting healthcare expenditure. From the coefficients of the selected model, the relative weights of each group were calculated to set a case-mix in each health district.
Results: Models based on multimorbidity-related variables better explained integrated healthcare expenditure. In the first part of the two-part models, a logit model was used, while the positive costs were modelled with a log-linear OLS regression. An adjusted R^2 of 46–49% between actual and predicted values was obtained. With the weights obtained by CRG, the differences found with the case-mix of each health district proved most useful for budgetary purposes.
Conclusions: The expenditure models allowed improved budget allocations between health districts by taking into account morbidity, as opposed to budgeting based solely on population size.

1. Introduction

The demographic change that the more developed countries, such as Spain, are undergoing and which is characterised by increased life expectancy and population ageing, is a major challenge that threatens the sustainability of both state health care systems and the welfare state. The main consequence of this new population configuration is the higher prevalence of chronic diseases, given the phenomenon of multimorbidity [1–3]. Together with the negative outcomes associated with multimorbidity, such as mortality, disability and deficient quality of life, we also see an increase in associated costs.

Predicting healthcare expenditure according to morbidity gives rise to two methodological questions: how to measure multimorbidity and which predictive models to choose. Regarding the former, a valid alternative is to use a risk adjustment system. Risk adjustment systems were developed to determine the multimorbidity profile and the population's general health status in order to establish capitation payment in medical service provision and better planning for health services. These systems are based on the diagnostics registered in electronic health databases and each individual is classified into a multimorbidity group. The most widely used patient classification systems for risk adjustments in health based on diagnostics are: Adjusted Clinical Groups (ACG) [4], Diagnostic Cost Groups (DCG) [5,6] and Clinical Risk Groups (CRG) [7].

CRGs have been applied to budgetary planning [8], to the comparison of health service utilization and expenditure between different risk groups [9,10] and to the identification of high cost complex patients [11–14].

In this work, we use CRG as measure of multimorbidity. The CRG system classifies patients into different morbidity groups through disease codes from an electronic health record, using individual information on acute episodes and treatments for chronic conditions. From this information, each person is assigned to one of the 1076 (depending on the version) CRGs. Each group is mutu-

Abbreviations: ACG, Adjusted Clinical Groups; ACRG3, Aggregated Clinical Risk Groups 3; CRG, Clinical Risk Groups; DHD, Denia Health District; GLM, generalised linear models; MHS, mean health statuses; MAPE, Mean Absolute Percentage Error; MEDAPE, Median Absolute Percentage Error; RMSE, Root Mean Square Error; OLS, Ordinary Least Squares; R^2, coefficient of determination; PHC, primary health care; VC, Valencian Community.

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ally exclusive and each individual is classified into categories with common clinical characteristics and similar consumption patterns. Moreover, each group can, in turn, be grouped into different aggregates as one of nine CRGs or mean health statuses (MHS). These nine MHS contain at least six levels that identify each group's severity, though some CRG groups consider only five, four or two. The aggregation level that considers the nine MHS and the six severity levels is called an Aggregated Clinical Risk Group 3 (ACRG3) [7].

The second concern addresses how to model healthcare expenditures, as these dependent variables typically have distributions which show right-skewness with a large mass at zero [15].

Ordinary least squares (OLS) lineal regression based on normal distribution has traditionally been used [4,16–18]. To correct the right-skewness of healthcare expenditure, early approaches considered a transformation of the data, such as a logarithmic transformation through an OLS regression model. However, there is a risk of the error term of model. To solve this, it is possible to go from the E(ln(y/x) to the ln(E(y/x) by retransformation [19,20]. Other authors have begun to use generalized linear models (GLM) [21–27]. GLM methodology offers advantages over OLS regression: 1) the data dealt need not follow a normal distribution, nor meet homoscedasticity criteria; 2) it provides estimates of the ln(E(y/x) and E(y/x) directly, without any requirement for retransformation [28]. GLM are characterised by the possibility of adopting different types of probability distributions (Gamma, Poisson, Binominal, etc.).

Another problem in analysing healthcare expenditure is a possible large mass of observations with zero-cost [29]. Different studies have adopted different solutions for this: 1) adding a positive constant k to the costs, thus modelling the log(cost + k), usually in an OLS framework [8]. This has the previously mentioned problem of back-transformation [19], which can be avoided by using GLM and not taking into account different behaviours of patients with zero-costs. 2) using the Tobit model based on the concept of latent variable. 3) using a mixed model that explicitly takes into account the different nature of the populations, one with positive and the other with zero-cost [30]. The expectation is split in two parts, the first modelling the probability of any expenditure, based on the full sample. The second models the actual level of expenditure conditionally to c>0. Here, the following distinctions are made [31]: 1) if the distribution allows for zeros, then those models with a separate zero cost mechanism are called zero-inflated models; 2) if the distribution does not allow for zeros, those models with a separate zero cost mechanism are commonly called two-part models. The two-part model is based on a statistical decomposition of the density of the outcome into a process that generates zeros and a process that generates positive values [15].

It must be kept in mind that the two-part models can also have the problem of retransformation if the second part of the model is based on a transformation, e.g. a logarithmic transformation. To avoid this, the substitution of the OLS model part for a Gamma model is a valid option [29].

In Spain, CRG is used by various autonomous regions and organisations: the Basque country, the Valencian Community (VC) [32,12,3] and the *Baix Empordà* (Girona) [11,33–36]. In these cases, the regression models used are adjusted by OLS either in their original form or through the logarithmic transformation of the dependent variable. More recently, the integrated cost of patients with expenditure other than zero has been modelled using GLM [37], as has the pharmaceutical prescription expenditure using a variant of CRG called adjusted morbidity groups (AMG) [38].

Thus, the two main purposes of this article are: 1) to model the expenditure of integrated health care (hospital, primary health care (PHC) and pharmaceutical prescription) for the entire population of a health district of the VC according to multimorbidity, using CRG. 2) to show how the predictive model is applied to the allocation of health budgets.

Previous works carried out in the VC [32,39] have modelled the pharmaceutical expenditure for the whole population. However, the present work models the total health expenditure and, moreover, the expenditure for the whole population (0 cost included), which represents a new contribution compared with a previous work carried out in Girona [33].

The availability of a system that relates multimorbidity and expenditure is a highly relevant innovation for some health systems. As well as establishing predictive budgets at different levels of the system for the health district, health centre and practitioner, it can be used to assign other resources, such as human resources.

2. Materials and methods

2.1. Design and study area

This is a cross-sectional study of total healthcare expenditure and its application in clinical management using predictive models. A database of the 156,811 inhabitants was available that make up the Denia Health District (DHD) of the VC that is managed according public–private partnership agreement [12]. For each individual, the database contains age, sex, MHS, severity level, pharmaceutical expenditure (in euros), PHC expenditure (in euros) and hospital expenditure (in euros). All data was taken from 2013.

2.2. Sources of information

From the Regional Ministry of Health (*Conselleria de Sanitat*), the information sources on the patients are: the *Population Information System* (SIP), which holds the identifying and demographic variables of the patient; the *Ambulatory Information System* (SIA-GAIA), which gathers the pharmacy prescriptions expenditure and PHC activity; and the *Patient Classification System,* which classifies the patient into a CRG (standard version 1.6). This information is available for all the health districts, including DHD.

Information on hospital expenditure for the DHD was provided by the Denia Hospital Management Control services, and includes costs for hospitalisation, surgery, outpatient consultations, laboratory, medical imaging, outpatient oncology care, dialysis and referrals to other hospitals. PHC expenditure was not obtained directly from the accountancy services of the Regional Ministry of Health, but was calculated from the official prices according to the Public Tariffs Law (*Ley de Tasas*) of the VC [40] and the number of contacts made with the health service.

2.3. Modelling

We used two-part models to estimate four dependent variables: total healthcare expenditure, pharmaceutical prescription expenditure, PHC expenditure and hospital expenditure. Only the predictions for total healthcare expenditure were used to construct a capitation model and assign budgets to VC health districts.

With two-part models there are four main modelling choices [15]. The first is to select the first part of two-part model. The first part is usually modelled via a probit:

$$P_r\left(c_i > 0/x_i\right) = \phi\left(x \cdot \beta\right) \quad (1)$$

Where ϕ represents the standard normal cumulative distribution function, or via a logit:

$$P_r\left(c_i > 0/x_i\right) = \frac{e^{\alpha+\beta\cdot x}}{1+e^{\alpha+\beta\cdot x}} \quad (2)$$

We chose a logit model to define the probability of costs greater than 0. The second and third choices correspond to the modelling of positive costs, using the Manning and Mullahy algorithm [28,37,41].

Distributions considered for the positive costs are an appropriate model in the log-linear OLS or the GLM class with a log link:

$$\text{Log-linearOLS}: Logc_i = \alpha + \beta X_i + \varepsilon_i \quad (3)$$

$$\text{GLMwithaloglink}: c_i = e^{\alpha + \beta X_i + \varepsilon_i} \quad (4)$$

The final result of the two-part model is obtained by [29]:

$$E\left(c_i/x_i\right) = P_r\left(c_i > 0/x_i\right) E\left(c_i/x_i, c_i > 0\right) \quad (5)$$

The fourth choice concerns the specification of the linear index.

We further designed five models with different explanatory variables. Model 1: age and sex; Model 2: MHS and severity; Model 3: MHS, severity, age and sex; Model 4: ACRG3; Model 5: ACRG3, age and sex. The variables sex, ACRG3, MHS and severity were dummy variables. The variable sex took the value 1 if it was male and 0 otherwise.

We estimated the two-part model and statistical test in Stata, using the *twopm* command [42,43].

2.4. Specification tests, goodness of fit and validating the model

We tested the specification of the explanatory variables in the second part by conducting Pregibon's link test [44], a modified Hosmer–Lemeshow test [45], the Root Mean Square Error (RMSE), the Mean Absolute Percentage Error (MAPE), the Median Absolute Percentage Error (MEDAPE) and the adjusted coefficient of determination (R^2) between the logarithm of the current values and those predicted by the models.

Using the model for total healthcare expenditure, an estimated total expenditure for each value of the explanatory variables was obtained. To corroborate that the selected model was also the one with the strongest predictive power for the total actual expenditure, the mean predictive of total actual cost by decile will be calculated. Also we will plot the predicted means across the range of predicted values for the predictive total expenditure per decile. This enables visual detection of the MHS that have greater variability than the mean [41].

2.5. Obtaining weights and case-mix system

The weights of each multimorbility group were obtained from the quotient between the healthcare expenditure of each multimorbility group and the healthcare expenditure of the healthy group. These weights were used to obtain the adjusted patients for each district in the VC (number of individuals of each ACRG3*weight of ACRG3) and their case-mix (adjusted patients/total population) for adjusted capitation budgeting purposes.

This research was approved by the Behavioural Research Ethics Board at the Generalitat Valenciana on January 30, 2014, with protocol code RUTFAR- 2013-01, version of 19 December 2013. The Research Commission of Denia Health District approved the project on 12 February 2015.

3. Results

3.1. Descriptive analysis

Table 1 shows the number of individuals, average age, female population and total healthcare expenditure (€/inhabitant) for each MHS and severity level. The patients with the highest average expenditure were those in MHS 9, with an average of €14,423.

Generally, the total average healthcare expenditure increases with the number and intensity of chronic diseases. The high standard deviation and a median value that was notably lower than the average in each MHS indicates wide variability in expenditure and a high concentration in a small part of the population. The average age also increases systematically with the number of chronic diseases, going from 33.8 years old for the healthy status to reach 75.9 in MHS 7. However, in MHS 8 and 9, which refer to malignant diseases and catastrophic conditions with a strong economic impact (cystic fibrosis, transplants, etc.), the average age descends, as these conditions are less tied to an age group than the other chronic conditions in MHS 6 and 7. MHS 9 with severity level 6 is the MHS with the highest average expenditure (€42,881). ACRG3 10, the healthy group, represents 54.7% of the total population.

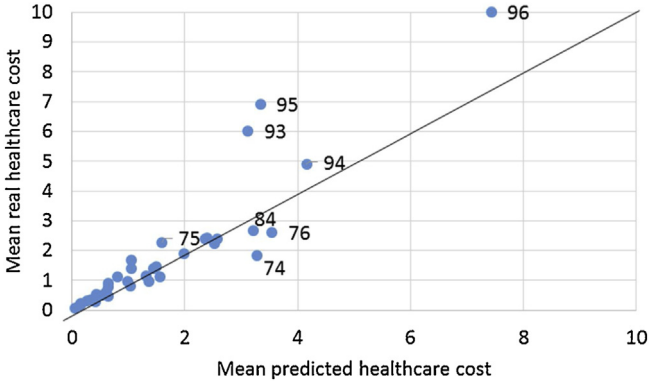

Fig. 1. Mean prediction of actual total healthcare cost of ACRG3 by decile.

3.2. Econometric modelling of healthcare expenditure according to morbidity

The first modelling of the probability of any expenditure does not require a decision on the model to be chosen. Table 4, therefore, includes only results from the model selected. Table 2 shows the test results by model selection for second part between the five models designed with different explanatory variables. In all cases the kurtosis of residual analysis (log scale) of the GLM log-link estimator were higher than 3. This means that, according to the algorithm used, we must conduct log-OLS estimation instead of GLM. According to results of the modified Hosmer-Lemeshow, Pregibon's link and MEDAPE, model 4 achieved the highest level of specification. This model, which included the 37 multimorbidity groups of ACRG3 aggregation level as independent variable, had an adjusted R^2 of 46.4%, which was not the highest, but sufficient. Therefore, we used this model for analysing the other cost dependent variables and designing the predictive case-mix system for the health district's budget assignation.

The test results of the model's estimation for pharmaceutical prescription, PHC and hospital expenditures are shown in Table 3. The pharmaceutical predictive model achieved the best results with 55.6% of adjusted R^2. All models had a good specification.

In Table 4 (columns 2 and 3) we show the results from the two-part models for total healthcare expenditure, using multimorbidity groups classified by ACRG3. To obtain the predicted expenditure value for each group we retransformed the coefficients and also considered Duan's smearing estimator (1757) (column 4). Column 5 of Table 4 shows the total healthcare expenditure estimated from multiplying non-zero probability obtained from column 2 by the value of column 4.

Fig. 1 illustrates the predicted means across the range of predicted values for the predictive total expenditure per decile. The actual decil means form a 45° line. However, all groups of MSH 9 and group of MSH 7 which indicates they are under-predicted, while others (ACRG3 74, ACRG3 76 and ACRG3 84) fall below the line, which indicates they are over-predicted.

Table 1
Average total healthcare expenditure and population distribution by mean health status and severity level.

Mean Health Status		Severity level							
		0	1	2	3	4	5	6	Total
1 Healthy	Population (%)	85,668 (54.7%)							**85,668 (54.7%)**
	Mean age	33.8							**33.8**
	Female Population (%)	47.9%							**47.9%**
	Health Cost (€/inhab) Mean (SD)	240 (750)							**240.0 (750)**
2 History of Significant Acute Disease	Population (%)	6142 (3.9%)							**6142 (3.9%)**
	Mean age	36.9							**36.9**
	Female Population (%)	57.7%							**57.7%**
	Health Cost (€/inhab) Mean (SD)	1013.1 (2936)							**1013.1 (2936)**
3 Single Minor Chronic Disease Level	Population (%)		14,805 (9.4%)	805 (0.5%)					**15,610 (9.9%)**
	Mean age		47.5	42.9					**47.3**
	Female Population (%)		56.2%	65.7%					**56.7%**
	Health Cost (€/inhab) Mean (SD)		632.9 (1781)	1549.0 (4636)					**680.1 (2039)**
4 Minor Chronic Disease in Multiple Organ Systems	Population (%)		4088 (2.6%)	1425 (0.9%)	988 (0.6%)	106 (0.1%)			**6607 (4.2%)**
	Mean age		56.6	62.1	58.6	59.7			**58.1**
	Female Population (%)		63.7%	70.2%	76.9%	78.3%			**67.4%**
	Health Cost (€/inhab) Mean (SD)		931.8 (1400)	1288.1 (1672)	1629.9 (2061)	2168.2 (1618)			**1133.9 (1605)**
5 Single Dominant or Moderate Chronic Disease	Population (%)		18,364 (11.7%)	4495 (2.9%)	1483 (0.9%)	183 (0.1%)	313 (0.2%)	12 (0.0%)	**24,856 (15.8%)**
	Mean age		54.6	57.3	61.1	72.6	68.5	60.2	**55.8**
	Female Population (%)		52.1%	52.9%	42.3%	41.5%	49.2%	33.3%	**51.5%**
	Health Cost (€/inhab) Mean (SD)		1360.4 (2615)	1990.8 (2908)	2663.0 (4040)	4806.2 (21,399)	3301.9 (4477)	5962.2 (8517)	**1604.2 (3384)**
6 Significant Chronic Disease in Multiple Organ Systems	Population (%)		8244 (5.3%)	3606 (2.3%)	2137 (1.4%)	1202 (0.8%)	480 (0.3%)	37 (0.0%)	**15,706 (10.0%)**
	Mean age		67.6	70.2	71.8	74.0	75.8	73.1	**69.5**
	Female Population (%)		57.4%	50.3%	50.2%	50.4%	47.9%	54.1%	**54.0%**
	Health Cost (€/inhab) Mean (SD)		2337.1 (3168)	3468.6 (5003)	4182.3 (5550)	4924.8 (5210)	5964.1 (6080)	10,244.7 (9801)	**3176.5 (4443)**
7 Dominant Chronic Disease In Three or More Organ Systems	Population (%)		292 (0.2%)	219 (0.1%)	423 (0.3%)	96 (0.1%)	39 (0.0%)	10 (0.0%)	**1079 (0.7%)**
	Mean age		74.4	75.5	76.6	78.8	76.2	68.6	**75.9**
	Female Population (%)		45.2%	40.6%	42.8%	46.9%	20.5%	30.0%	**42.4%**
	Health Cost (€/inhab) Mean (SD)		3894.4 (4388)	4863.0 (4078)	6242.8 (6782)	8122.9 (9333)	9780.4 (6891)	11,230.0 (11,967)	**5667.6 (6297)**
8 Dominant, Metastatic, and Complicated Malignancies	Population (%)		107 (0.1%)	249 (0.2%)	226 (0.2%)	81 (0.1%)	23 (0.0%)		**686 (0.4%)**
	Mean age		58.1	63.7	65.6	66.9	63.3		**63.8**
	Female Population (%)		49.5%	52.6%	31.9%	42.0%	69.6%		**44.6%**
	Health Cost (€/inhab) Mean (SD)		7138.8 (13,497)	9657.3 (12,252)	10,445.9 (12,752)	11,475.0 (12,752)	10,194.7 (6241)		**9757.9 (16,917)**
9 Catastrophic Conditions	Population (%)		59 (0.0%)	221 (0.1%)	87 (0.1%)	59 (0.1%)	28 (0.0%)	11 (0.0%)	**463 (0.30%)**
	Mean age		44.6	48.3	60.2	57.5	61.0	64.0	**49.6**
	Female Population (%)		44.1%	29.9%	43.7%	30.5%	28.6%	44.4%	**34.6%**
	Health Cost (€/inhab) Mean (SD)		4163.8 (5427)	7835.8 (4088)	25,808.3 (19,087)	21,020.0 (26,165)	29,615.7 (16,384)	42,880.7 (25,373)	**14,423.4 (16,917)**
TOTAL	Population (%)								**156,811 (100.0%)**
	Mean age								**43.8**
	Female Population (%)								**51.1%**
	Health Cost (€/inhab) Mean (SD)								**982.8 (2935)**

Table 2
Manning-Mullahy algorithm results: Model choice for second part modelling of the positive total healthcare expenditure.

Explanatory variables	N	Kurtosis	Model	Hosmer-Lemeshow (p-value)	Pregibon link (p-value)	Adjusted R^2	RMSE	MAPE	MEDAPE
Model 1 Age and sex	127,072	6.68	Log-OLS	58.53 (0.000)	4383.64 (0.000)	0.133	1.37	0.19	0.15
Model 2 MHS and severity	127,072	4.67	Log-OLS	25.28 (0000)	384.28 (0.000)	0.491	1.04	0.15	0.11
Model 3 MHS, severity, age and sex	127,072	4.69	Log-OLS	101.74 (0.000)	466.10 (0.000)	0.494	1.05	0.15	0.11
Model 4 ACRG3	127,072	4.97	Log-OLS	0 (1.000)	0 (1.000)	0.464	10.75	0.17	0.11
Model 5 ACRG3, age and sex	127,072	4.59	Log-OLS	87,03 (0.000)	27.61 (0.000)	0.467	10.34	0.17	0.11

Table 3
Manning-Mullahy algorithm results: Model choice for second part modelling for each positive expenditure type with ACRG3 independent variables.

Dependent Variables	N	Kurtosis	Model	Hosmer-Lemeshow (p-value)	Pregibon link (p-value)	Adjusted R^2	RMSE	MAPE	MEDAPE
Pharmacy	103,273	3.27	Log-OLS	0 (1.000)	0000 (1.000)	0.556	1.35	0.45	0.19
PHC	124,703	4.20	Log-OLS	0 (1.000)	0000 (1.000)	0.386	0.99	0.14	0.11
Hospital	88,684	4.27	Log-OLS	0 (1.000)	0000 (1.000)	0.330	2.10	0.25	0.20

Table 4
Estimation of the relative weights of the ACRG3 from the results of the two-part model.

(1)	First part Logit coefficients (2)	Second part Log OLS coefficients (3)	Exp (Coefficients + Constant (2))*Smearing Estimator (1757) (4) (Euro)	Estimated value (5) = P(c>0)*(4) (Euro)	Relative weight (6) = (5)/185.6
Constant	0.78	7.778			
ACRG3 1	0.00	−2.741	270.6	185.6	1.00
ACRG3 2	5.84	−1.578	865.1	862.6	4.65
ACRG3 31	2.47	−1.851	658.5	607.0	3.27
ACRG3 32	Omitted *	−0.810	1858.3	1858.3	10.01
ACRG3 41	4.04	−1.376	1059.5	1041.2	5.61
ACRG3 42	5.48	−0.985	1565.5	1559.0	8.40
ACRG3 43	Omitted *	−0.721	2039.0	2039.0	10.99
ACRG3 44	Omitted *	−0.360	2924.7	2924.7	15.76
ACRG3 51	3.34	−1.191	1274.4	1230.8	6.63
ACRG3 52	4.42	−0.703	2076.8	2052.2	11.06
ACRG3 53	4.66	−0.387	2847.1	2820.4	15.20
ACRG3 54	4.49	−0.299	3108.6	3074.2	16.57
ACRG3 55	3.65	−0.142	3639.6	3547.6	19.12
ACRG3 56	Omitted *	0.843	9737.8	9737.8	52.47
ACRG3 61	5.11	−0.443	2692.4	2676.2	14.42
ACRG3 62	5.71	−0.075	3888.5	3875.6	20.88
ACRG3 63	5.87	0.121	4734.3	4721.0	25.44
ACRG3 64	Omitted *	0.365	6042.7	6042.7	32.56
ACRG3 65	Omitted *	0.547	7243.5	7243.5	39.03
ACRG3 66	Omitted *	0.000	4193.3	4193.3	22.60
ACRG3 71	Omitted *	0.131	4779.5	4779.5	25.76
ACRG3 72	4.70	0.431	6450.4	6392.4	34.45
ACRG3 73	Omitted *	0.636	7919.5	7919.5	42.68
ACRG3 74	Omitted *	0.840	9711.6	9711.6	52.33
ACRG3 75	Omitted *	1.127	12,944.2	12,944.2	69.75
ACRG3 76	Omitted *	0.789	9232.0	9232.0	49.75
ACRG3 81	3.27	0.012	4243.3	4088.4	22.03
ACRG3 82	3.44	0.619	7784.5	7541.9	40.64
ACRG3 83	4.73	0.842	9733.4	9648.5	51.99
ACRG3 84	3.70	1.154	13,295.1	12,975.5	69.92
ACRG3 85	Omitted *	1.253	14,674.4	14,674.4	79.08
ACRG3 91	3.38	−0.080	3869.0	3741.9	20.16
ACRG3 92	Omitted *	0.953	10,872.6	10,872.6	58.59
ACRG3 93	Omitted *	2.061	32,943.0	32,943.0	177.52
ACRG3 94	Omitted *	1.687	22,648.7	22,648.7	122.05
ACRG3 95	Omitted *	2.260	40,190.5	40,190.5	216.58
ACRG3 96	Omitted *	2.655	59,627.0	59,627.0	321.32

$P(c > 0) = \frac{e^{cons+coefficent(2)}}{1+e^{cons+coefficient(2)}}$.

Note Table 4:
(*omitted) Groups with positive cost values only (P(c>0) = 1).
Column 2: Logit regression coefficients according to the equation [2].
Column 3: Log OLS regression coefficients according to the equation [3].
Column 4: Retransformed values of coefficients of column 3 multiplied by the smearing estimator.

3.3. Development of a case-mix model

The process for the calculation of the weights to establish the case-mix system by multimorbidity groups is given in the last column of Table 4. From the value of column 5, the relative weight is calculated in column 6.

Once the relative weights for each ACRG3 have been calculated, they are multiplied by the number of existing patients in each group of each VC health district to obtain the number of patients adjusted by morbidity. Dividing the value obtained in each health district by the number of total patients for that health district provides the case-mix. The results of these calculations are shown in Fig. 2.

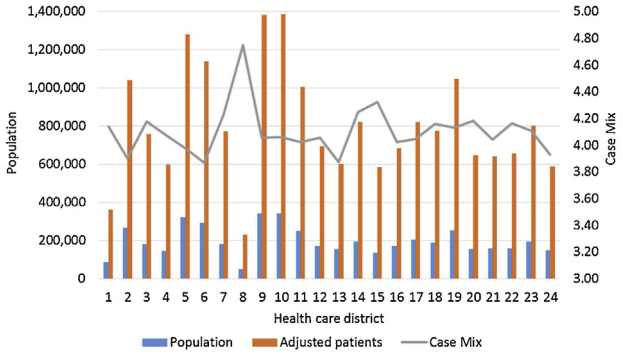

Fig. 2. Case mix, population and adjusted patients for each health district in Valencian Community.

The districts with higher morbidity will require higher capitation financing. The case-mix oscillates between 3.8 and 4.8.

4. Discussion

The direct predecessor of this study was a modelling of pharmaceutical prescription expenditure from CRG stratification, which was also carried out in the VC [32,46]. However, the main contribution of the present work is to analyse not only prescription pharmaceutical expenditure, but also expenditure in PHC and hospital settings, both together and separately, for the entire population of 156,811 in a health district of the VC, which signifies a notable advance in healthcare expenditure modelling.

In this work we use a two-part model [15] as opposed to the log (cost + k) in an OLS with which previous works were carried out [32,46], and in other works [16,47,48]. In the second part of the model, log-linear OLS were always chosen, both for the different models of total expenditure and the different categories of expenditure, as opposed to other works where GLM has sometimes been chosen [36,41].

The adjusted R^2 of 46.4–49.4% were similar to that obtained in other previous studies that used different patient classification systems. For example, a study carried out in Canada [16] used OLS regression and measured the explanatory and predictive quality of ACGs for total healthcare expenditure, which was 40%. Likewise, another study in Taiwan [47], relating total healthcare expenditure and ACGs through OLS regression, obtained an R^2 of 41.1%.

An R^2 of 48.3% in pharmaceutical expenditure has been obtained by OLS regression, using a sample of 81,873 individuals in Spain [48], which is a similar figure to that of the present work. Nevertheless, it is important to note that the above – mentioned study only encompassed those patients in contact with the healthcare system, either out – or inpatients, which means that their research did not reflect those subjects who did not use the healthcare system. Conversely, our work covered the whole population in the DHD, including those inhabitants with a zero cost, providing another important contribution.

Hospital expenditure had the lowest adjusted R^2 (33%) of the three main expenditure categories, due to treatment of acute conditions requiring surgery, hospitalisation and cancer treatment, among others. This wide variability in the same MHS is because not all chronic patients classified in one group require hospitalisation. Thus, for example, a patient from MHS 6 may present a series of complications, while another from the same MHS might not. This means hospital expenditure is more heterogeneous in any given MHS with the same severity level, as even the same disease may require a different number of hospitalisation days, several types and numbers of surgical interventions, etc. Those patients also classified within the MHS may register hospital expenditure for a musculoskeletal system or some other condition. We must also take into account that pregnant women, classified in the healthy status, also use hospital resources during their pregnancy and delivery. On the other hand, pharmaceutical prescription expenditure had the best adjusted R^2 (55.6%).

The analysis of expenditure by deciles shows a greater deviation for patients from MHS 9 and high severity levels. This may be due to these groups having a very low population and a high standard deviation. It may be the case that these groups are not fully represented in the models and new adjustments may be needed with elderly populations to ratify the obtained models.

There are great differences in the case-mix between the health districts, ranging from 3.8 to 4.8. Therefore, in terms of establishing a case-mix system for budget allocation, the model explained in this study might be a useful approach in future applications, as previously shown for pharmaceutical prescription expenditure adjusted by morbidity with CRG [8].

While the model presented by Monterde et al. [38] explained the pharmaceutical expenditure of the AMG using statistical GLM models adjusted to Poisson distribution, we concur with Inoriza et al. [35] on the methodological limitations of this proposal and the need to establish technical comparisons with models using CRG.

5. Limitations

The main limitation of this study was the population size considered, as it would have been desirable to have information on the total expenditure for the patients in various Health Districts. This, however, was not possible. Moreover, the PHC expenditure used in this study was obtained by applying an official standard tariff to the number of contacts made with this healthcare service, a figure obtained from estimations as this accounting information was also lacking. The case-mix model for the VC was established by extrapolating the weights obtained in the model for the DHD to the entire VC population. It would be recommendable for future research to be able to count on the whole population of the field of study.

Regarding the modelling, we chose model 4 according to results of the modified Hosmer-Lemeshow, Pregibon's link and MEDAPE. However, model 4 had the greatest RMSE. This RMSE would possibly be reduced by increasing the size of the sample by adding more health districts.

Another limitation, also regarding the information available, concerns home and long term residential care. This information was unavailable and therefore could not be included. This needs to be included in future studies to obtain the total healthcare expenditure. Other studies with a similar setting to ours [37] also lack this information.

Regarding external validity and extrapolation of the results, two requirements must be met. Firstly, that the multimorbidity classification system used is CRG, and secondly, that the cost structure is similar. However, the methodology and system offered in this work can be replicated with another kind of variables.

In any case, considerable variability exists in the typology of research and tools used for clinical risk adjustment. Thus, it would be worthwhile for more healthcare administration institutions to conduct studies in this field in order to be able to compare results and obtain feedback [35].

6. Conclusions

Multimorbidity grouping obtained from CRG patient classification system is a valid measure to predict healthcare expenditure. Good predictive power was achieved for pharmaceutical expenditure and total healthcare expenditure. Two-part models provided better estimations than other econometric models used for modelling healthcare expenditures.

Competing interests

The authors declare that they have no competing interests.

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Authors' contribution

These authors contributed equally to this work.

Ethics approval and consent to participate

All the information remained anonymous according to data protection regulations (Organic Law 15/1999 and Royal Decree 1720/2007). Our observational study was approved by the Behavioural Research Ethics Board at the Generalitat Valenciana (Comité Ético de Investigación Clínica Corporativo de Atención Primaria de la CV, CEIC) and the Research Committee of the DHD.

The need for consent to participate was deemed unnecessary as anonymised patient-level data were used in this study. Approval for using data was obtained from the Valencian Health Agency (reference no. ID001036).

Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available due confidentiality of the data but are available from the corresponding author on reasonable request.

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