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Estimating and planning hospital costs of public hospitals in Brazil

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Abstract: While the estimate of hospital costs concerns the past, its planning focus on the future. However, many public hospitals in low and middle-income countries don't have robust accounting health systems to evaluate and project their expenses. In Brazil, public hospitals are funded based on government estimates of available hospital infrastructure, historical expenditures and population needs. However, these pieces of information are not always readily available for all hospitals. To solve this challenge, we propose a flexible simulation-based optimisation algorithm that integrates this dual task: estimating and planning hospital costs. The method was applied to a network of 17 public hospitals in Brazil to produce the estimates. Setting the model parameters for population needs and future hospital infrastructure can be used as a cost-projection tool for divestment, maintenance, or investment. Results show that the method can aid health managers in hospitals' global budgeting and policymakers in improving fairness in hospitals' financing.

Highlights

- There is a scarcity of hospital cost data in LMIC and Brazil.
- Many public hospitals are funded based on government estimates;
- We propose an integrated approach that estimate and plans hospital costs;
- The method was applied to a network of 17 public hospitals in Brazil;
- Results help policymakers in improving fairness in hospitals' financing.

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1. Introduction

Hospitals are complex and cost-intensive facilities of health care systems. In the last decade, health care expenditure in low and middle-income countries (LMIC) has been around 5.2% of the GDP [1]. Brazil spends around 9.5% of the GDP on health care, and hospitals' related costs as medical goods, outpatient, and inpatient care are substantial, about 2.0%, 2.5%, and 1.9% of the GDP, respectively [2].

In Brazil, nearly 40% of the expenditure on health care is public, and approximately 60% of public health care expenses are used to fund hospitals [3]. The majority (71%) of hospital capacity (432,715 beds) in Brazil is public, and funding hospitals is not a trivial task. Among public hospitals, 4% are federal, 25% are owned by states and 70% are owned by municipalities. Most municipality hospitals are small, with fewer than 50 beds, and present low levels of efficiency and effectiveness. Federal and state public hospitals are larger and have higher occupancy rates. To finance hospitals, the federal government has to estimate the total hospital cost based on available infrastructure, historical expenses and population needs. High complexity procedures are paid according to the volume of services. Based on such estimates, the federal government transfer funds to states and municipalities, and those pay hospitals on a fee-for-service basis [4]. A recent study used Data Envelopment Analysis to evaluate Brazilian hospitals operational efficiency based on financial aspects and capacity [5]. However, there is a lack of approaches that estimate the total cost of hospitals of different sizes and characteristics. Hospitals' cost estimation provides fundamentals for funding and fairness in financing these units when detailed operational and financial data is not fully available.

Classical studies often estimate hospitals' costs as a measure of hospital size, particularly the number of beds. Hence, the increase in hospital size would yield economies of scale since cost components like equipment, personnel, and infrastructure are of fixed nature [6, 7, 8]. However, a hospital cost increase is not only due to its size. Hospitals' costs grew from the 1950s to the 1970s, and Feldstein demonstrated that inflated expenses were due to excess demand [9]. The researchers advanced on total cost estimation moving from uni-dimensional to multidimensional measures. The estimate of hospital inpatient costs included variables dimension reduction, regression, and aggregation of explanatory variables [10, 11]. Researchers also observed that hospitals in more competitive environments presented significantly higher costs per patient than those in less competitive environments. It suggests that the competition between hospitals to attract physicians and patients leads to the acquisition of specialised clinical services, new procedures for patient diagnoses, and amenities attractive to patients, which increases the hospitals' costs [12, 13].

Recent contributions to the state-of-the-art are usually department-specific instead of estimating hospitals' global costs. Studies have shown the costs' variation in maternity care [14, 15], materials and supply expenses [16], operations [17], and readmission [18]. In general, the traditional economies of scale link the volume increase in a hospital service with reduced cost per patient in that service [19], or even on multiple services [20]. But recently, a study revealed an association between a high level of elective visits and increased emergency care costs [21], suggesting the need for more cost modelling in hospitals. The research on hospitals' costs by simulation optimisation, for instance, has occurred only at department-specific [22] and on the conceptual level [23]. The estimates of hospital total annual cost by finance reports or care processes perspective exist but are isolated. Therefore, we propose an integrated approach to estimating and planning hospitals' costs.

The first step consists in estimating the hospital's total costs. Therefore, we propose the cost classification into two groups, Cost Components (CC) and Care Modules (CM), and estimate their monthly expenditures by applying multiple linear regression. The method was applied to a network of 17 public hospitals in Brazil to produce the estimates. Hospital finance reports provide valuable information on expenses. Hence, CC represent the macro-structure of cost division based on standard classifications, such as personnel, third-party services, medical goods, depreciation, general expenses, and others. From a CC perspective, we refer the reader to studies that show, for instance, the relevant cost of nursing among hospitals' payroll expenses [24]; the depreciation charge included in hospitals' cost accounting [25], and the significant expenses of materials and supply [16]. On the other hand, the CM perspective considers costs associated with services provided. Consequently, CM derives from the aggregation of productive cost centres into service blocks, such as clinical services, inpatient and outpatient services, urgent care, emergency care, paediatric service, adult ICU, maternity care, and others. From a CM perspective, publications show that clinical services have high fixed costs directly influencing the cost of care in the hospital [12]; Inpatient and outpatient care are elements to evaluate the hospitals' costs structure through a multiple output analysis [26]; The cost of emergency is high, but non-urgent care costs in the emergency department are relatively low compared to urgent care [27]. Moreover, maternity services presented low utilisation due to hidden costs of the system [14] and high variation in costs between high-quality hospitals in safe maternal care systems [15]. Concerning ICU services, the paediatric ICU costs were most related to patients' average length of stay (ALOS) and the severity of illness. The ICU costs were also associated with higher laboratory and diagnostics costs [28]. Few studies adopt dual approaches to estimate hospitals' total annual costs [29, 30]. The cost estimate may occur on a detailed level of micro-costing accounting, which is time-consuming, or on the aggregate level by using multivariate regression analysis.

The following step consists in planning future costs for budgeting. Therefore, we propose a simulation-based optimisation approach, that includes a goal programming model and a Monte Carlo simulation to plan hospital costs. The parameters can be adequately adjusted fitting historical hospitals' costs and validating the model. Following this, managers can change the model optimisation goals and operational parameters to conduct budgeting and capacity planning in the future. Monte Carlo stochastic simulation is a well-defined OR methodology to describe the behaviour of systems with random effects. It has proved its usefulness in hospital costs analysis [31] and hospitals' operations [17, 32]. For estimating the future hospitals' costs, however, Monte Carlo simulation does not provide strategies to optimise its operations, design, or capacity use. Nonprofit or for-profit hospitals' residual claimants may be the decision-maker, doctors, employees, patients, or even donors, and they may diverge about personnel, resources, department expenses, or the following year's reserve [33, 34]. Therefore, we propose a simulation-based optimisation approach to provide flexibility for hospitals' cost planning. The model considers capacity [35] and the need for permanent staff [36] from an aggregate perspective.

Dimensioning the patients' demand for health care or the health care requirements for Brazilian public hospitals is not within the scope of this work. Planning such integrated health care would require: (i) a demand criterion that satisfies the members of society; (ii) a holistic view of available health services; (iii) the location and distribution of resources; and (iv) a consensus about a projected efficiency and effectiveness for each element of the hierarchical health care system. In this paper, we ignore these difficulties and concentrate our efforts on estimating and planning the annual cost of public hospitals. The following section (Section 2) shows the proposed modelling approach. We applied the method to 17 public hospitals. The results are presented in Section 3. Finally, Section 4 concludes the research with directions for future efforts.

2. Method

2.1. Estimating hospital costs

There is a scarcity of hospital cost data in LMIC. Therefore, the first activity is assigning the aggregate cost data into broad CC and CM categories through a traditional step-down cost accounting (SDCA). The approach should contemplate the whole spectrum of expenditures [37]. The method is relatively simple for generating cost data for hospitals. We applied SDCA for a general public hospital with 50 beds, medium complexity, and 250 employees (see the supplemental material). The CC can comprise personnel, third-party service, medical goods, equipment, overheads, and others. The CM should include costs of comparable activities among hospitals to enable the comparison between them. However, hospitals are complex environments with multi-functional professionals working in different cost centres in a contingent way. Therefore, SDCA can produce an overly simplified distribution of hospital personnel expenses over the cost centres.

In the case of plenty of data available, the quantitative data in the databases deriving from hospitals allows its parametric analysis. Our database allows its parametric analysis since it contains ten years of records (Jan/2010 to Dec/2019) deriving from a convenient sample of 17 public hospitals. The data on 75 hospital cost drivers (see Table A1 in Appendix A) were classified into CC and the CM. Due to multicollinearity, we applied factor analysis to reduce the dimensionality of original variables into a few independent and explanatory variables (see Table 1). Personnel expenses are a common component of both CC and CM. Following this, we used multiple linear regression to estimate the cost functions for CC and CM.

Table 2 and Table 3 presents the hospital cost estimate for CC and CM. We use multiple linear regression to estimate the functions' independent coefficients $\beta_1, ..., \beta_{26}$. The functions describe the average monthly expenditure on resource j, setting a ED_j parameter. The resource j of CCs include (1) Personnel, (2) Third-party services, (3) Medical Goods, (4) General Expenses, (5) Depreciation, and (6) Other.

The resource j of CMs include (1) Personnel, (2) Outpatient, (3) Medical Clinic, (4) Urgency and Emergency, (5) Surgical Clinic, (6) Adult ICU, (7) Paediatric ICU, (8) Maternity, (9) Neonatal ICU, and (10) Other. The coefficients $\gamma_1, ..., \gamma_{30}$ of the functions define the characteristics of a hospital. The blocks "Other" present in both CC and CM are the aggregations of cost elements unrelated to the blocks of each approach. The R^2 presented the results from the multiple linear regression where the independent coefficients are the mean value of the distribution. The resulting cost functions approach sets ED_j optimisation models' stochastic parameters for CC and CM. They are presented in Table 4.

Table 1. Independent and explanatory variables related to CC and CM

CC	Parameters Description	Unit
NA	Number of nursing assistants	employee
ICU	Number of ICUs	ICU
IE	Number of diagnostic imaging equipment	equipment
CT	Number of CT scanners	equipment
$\beta_1 \dots \beta_{26}$	Cost function coefficients described from data analysis	scalar
CM	Parameters Description	Unit
EV	Emergency room visits	patient
HCP	Hospital admissions for clinical procedures	patient
HSP	Hospital admissions for surgical procedures	patient
$HICA^a$	Hospital admission to adult ICUs	patient
$HICA^n$	Hospital admission to Neonatal ICUs	patient
HOB	Hospital obstetrics admission	patient
HO	Hospital outpatient admission	patient
SB	Number of surgical beds in the hospital	bed
ICU^a	Number of adult ICU beds in the hospital	bed
ICU^n	Number of neonatal ICU beds in the hospital	bed
$ALOS^{hc}$	Average length of stay in hospital	day
$\gamma_1 \dots \gamma_{30}$	Cost function coefficients described from data analysis	scalar

Table 2. Multiple linear regression estimate for hospital Cost Components (CC).

CC parameter cost function	R^2
$ED_1^{cc} = \beta_1 EN + \beta_2 HB + \beta_3$	0.93
$ED_2^{cc} = \beta_4 EN + \beta_5 HB + \beta_6 CB + \beta_7$	0.79
$ED_3^{cc} = \beta_8 EH + \beta_9 PD + \beta_{10} HA + \beta_{11}$	0.87
$ED_4^{cc} = \beta_{12} NA + \beta_{13} EN + \beta_{14} HB + \beta_{15} HI + \beta_{16}$	0.80
$ED_5^{cc} = \beta_{17} IE + \beta_{18} CT + \beta_{19} ICU + \beta_{20} CB + \beta_{21} PD + \beta_{22}$	0.79
$ED_6^{cc} = \beta_{23} NA + \beta_{24} CB + \beta_{25} IE + \beta_{26}$	0.73

Table 3. Multiple linear regression estimate for hospital Care Modules (CM).

CM parameter cost function	R^2
$ED_1^{cm} = \gamma_1 EN + \gamma_2 HB + \gamma_3$	0.93
$ED_2^{cm} = \gamma_4 ALOS^{hc} + \gamma_5 CB + \gamma_6 HO + \gamma_7$	0.55
$ED_3^{cm} = \gamma_8 PD + \gamma_9 HCP + \gamma_{10}$	0.71
$ED_4^{cm} = \gamma_{11} SB + \gamma_{12} EV + \gamma_{13} HB + \gamma_{14}$	0.90
$ED_5^{cm} = \gamma_{15} HSP + \gamma_{16}$	0.89
$ED_6^{cm} = \gamma_{17} ICU^a + \gamma_{18} HICU^a + \gamma_{19}$	0.91
$ED_7^{cm} = \gamma_{20} PD + \gamma_{21}$	0.05
$ED_8^{cm} = \gamma_{22} ICU^n + \gamma_{23} HOB + \gamma_{24}$	0.79
$ED_9^{cm} = \gamma_{25} ICU^n + \gamma_{26} HICU^n + \gamma_{27}$	0.76
$ED_{10}^{cm} = \gamma_{28} EH + \gamma_{29} CB + \gamma_{30}$	0.82

2.2. Planning hospital costs

The proposed simulation-based optimisation uses Monte-Carlo simulation to develop scenarios. It randomly selects a value from the random variable in the parameters of an optimisation model that repeatedly solves the underlying program to analyse the collective results. Our optimisation problem is a goal programming model, a generalisation of linear programming and a branch of multi-objective optimisation. We opted not to develop an explicitly multi-objective approach to reduce the model complexity, providing a basic capability for scenario analysis. In the simulation-based optimisation, we draw new parameter data from random variables, then simulate multiple instances, run the optimisation problem for each scenario, and analyse the recorded results.

Let T be the types of hospitals, such as general, specialist, mixed unit, or day hospitals with a distinct distribution of personnel. Let i be the operating expenditure (OPEX) index for professional categories and j be the remaining OPEX indexes of each resources blocks (CC or CM), and let $k = 1, ..., K$ be the capital expenditures (CAPEX) in investment as large or technologically advanced equipment, infrastructure expansion, among others. Each hospital is composed of $j = 1, ..., J$ resource consumption sections representing CC or CM. Professional categories are indexed by $i = 1, ...q, m, n, ..., I$. Table 4 presents the parameters and variables used on CC and CM optimisation models.

The allocation of resources minimising the sum of the deviations in the objective function and operational constraints creates a hospital cost plan. The objective function is subject to constraints (1)-(11):

$$\begin{aligned} \text{Min} \quad & P_1 e^- + P_1 pc^- + P_2 \sum_{k \in K} rr_k^- + P_3 sa^- + P_4 sp^- \\ & + P_5 \sum_{i \in I} (ep_i^- + ep_i^+) + P_6 (mn^+ + dn^+ + dn^-) \end{aligned}$$

$$x_i - DE_{it} E + ep_i^- - ep_i^+ = 0 \quad \forall i \in I, t \in T \tag{1}$$

$$\sum_{i \in I} x_i + e^- - e^+ = E \tag{2}$$

$$\sum_{i \in I} SA_i x_i + pc^- - pc^+ = \beta_1 EN + \beta_2 HB + \beta_3 \tag{3}$$

$$y_j + de^- - de^+ = AED_j \quad \forall j \in J \tag{4}$$

$$\sum_{i \in I} \frac{WD x_i}{PD} + sp^- - sp^+ = EPP \tag{5}$$

$$\sum_{i \in 1..n} x_i - P_m x_m + mn^- - mn^+ = 0 \tag{6}$$

$$x_p - P_n x_n + dn^- - dn^+ = 0 \tag{7}$$

Table 4. Parameters and variables used in the CC and CM models

CC & CM	Parameters Description	Unit
E	Number of hospital employees (probability distribution)	employee
HB	Number of hospital beds	beds
ρ	Hospital occupancy rate (probability distribution)	scalar
PD	Hospital patient-days ($365(HB\rho)$)	patient-day
EH	Number of employees with higher education	employee
EN	Number of nurses	employee
CB	Number of clinical beds	beds
HA	Authorisation of hospital admissions (inpatient + outpatient)	patient
HI	Hospital inpatient admissions	patient
WD	Number of annual working days per employee (prob. dist.)	day
EPP	The proportion of employees per patient	scalar
P_i	The proportion among employees of category i for a service	scalar
DE_{it}	Distribution of employees of category i for hospital of type t	scalar
SA_i	The annual salary of professional of category i (prob. dist.)	$
SI_i	Salary increase for professional category i by inflation	scalar
ED_j	Average monthly expenditure by CC or CM j	$
EIE	Estimated inflation expenditure for the hospital (prob. dist.)	scalar
AED_j	Annual expenditure with CC or CM. $12[ED_j(1+EIE)]$	h
RD_k	Next year reserve for Investment Sector k	$
$P_1 \ldots P_6$	Weights associated with deviation from the goals	scalar
Variables	**Description**	**Unit**
x_i	Number of employees allocated to each category i	scalar
y_j	Annual expenses with resource block j	$
z_k	Reserve for the following year for investments of type k	$
e^-, e^+	Lack and excess of employees, respectively	scalar
pc^-, pc^+	Lack and excess of capital for paying personnel costs	scalar
de^-, de^+	Lack and excess of capital for resources blocks expenses	scalar
rr^-, rr^+	Lack and excess of a reserve for the following year	scalar
sa^-, sa^+	Lack and excess of capital for salary adjustment	scalar
sp^-, sp^+	Deviation in the proportion of employees and patients	scalar
ep^-, ep^+	Deviation in the employee's distribution by function	scalar
mn^-, mn^+	Deviation in the proportion of managers and nurses	scalar
dn^-, dn^+	Deviation in the proportion of doctors and nurses	scalar
dm^-, dm^+	Deviation in the proportion of doctors and managers	scalar

$$\sum_{i \in 1..n} x_i - P_q x_q + dm^- - dm^+ = 0 \tag{8}$$

$$x_m \geq P_n x_n \tag{9}$$

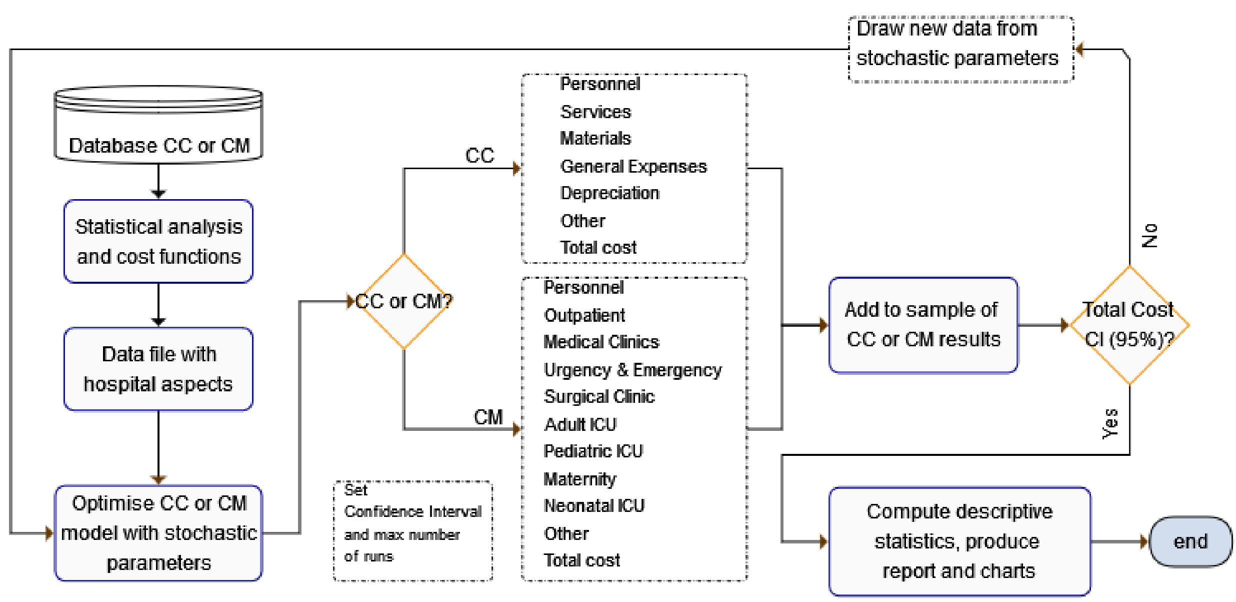
$$z_k + rr_k^- - rr_k^+ = RD_k \quad \forall k \in K \tag{10}$$

$$\sum_{i \in I} (SI_i SA_i x_i - SA_i x_i) + sa^- - sa^+ = z_k RD_k \tag{11}$$

The optimisation model minimises deviations from the goals considering all priority levels indexed from 1 to 6. The priorities consist of (P_1) guaranteeing the required personnel to provide adequate services to patients; (P_2) exchanging or purchasing new equipment for hospital services; (P_3) providing the annual salary adjustment for employees; (P_4) achieving the desired proportion of professionals per patient; (P_5) achieving the distribution of personnel in each category according to a tabulated value; (P_6) maintaining the proportions of professionals per employee.

The model includes constraints that fit the hospital's features and plans. Each type of hospital has its distribution of personnel, as described in equation (1). Constraints (2) and (3) define the requirement and the cost of employees, respectively. We estimate the personnel cost by multiplying the number of each professional full-time-equivalent (FTE) employee by the average yearly wage rate adjusted by an average tax rate. Constraint (4) sets the expected expenses for CC or CM. Lined up with the hospital services demand, the model establishes a fixed proportion of the total employees for each function. Constraint (5) represents the proportion estimates of employees per patient. The constraints include relationships commonly adopted in hospitals to maintain a service quality standard. Constraints (6)-(8) set proportions of nurse/manager, nurse/doctor, and doctor/manager. A hospital can set, for example, at least one management professional for every four nurses, one doctor for every ten nurses, and two management professionals for each doctor. Restrictions (9) produce fixed proportions between professionals, for instance, one manager per director, one coordinator per manager, two advisors per manager, four nurses per manager, at least one director, or one employee per position. Equation (10) plans the capital expenditures for the subsequent year. Such reserves are for hospital maintenance equipment, new medical equipment, such as MRI and CT scans, or a contingency fund for emergencies and epidemics. Finally, constraint (11) consists of the annual salary adjustment. In this case, the administrator makes a salary adjustment by a percentage for the categories. The model is activated within a simulation-based optimisation algorithm (see Figure 1).

Figure 1. Simulation-based optimisation algorithm for hospital cost planning.



Due to the inherent variability of sample data, some parameters of the optimisation model and the independent coefficient of the cost functions are modelled as random variables setting stochastic parameters of the CC or the CM optimisation model. Thus, the simulation draws new data from the random variables and calls the optimisation that trade-off metrics to provide the optimal allocation of resources, i.e., each simulation-optimisation round draws new data from random parameters and solves the underlying optimisation problem. The algorithm stops when the hospital's total annual costs reach a preset confidence interval. Otherwise, the algorithm iterates in a loop of optimisation rounds and increases the sample size with hospital costs. With previous conditions satisfied, the algorithm stops and produces the response variables presented by descriptive statistics (such as minimum, mean, standard deviation, median, maximum, coefficient of variance, and confidence interval). Algorithm 1 describes the simulation-based optimisation. The files are provided in the supplemental material.

Algorithm 1 Algorithm for hospital total annual cost estimation.

1: Define the CC or CM approach (in `config.py` file);
2: Define the hospital configuration parameters [a] (in `CC.dat` or `CM.dat` file);
3: Set expected Confidence Interval and maximum number of runs (in `config.py` file)
4: Start the simulation (in `sim-opt.py` file);
5: In the simulation call an optimisation run (in `simulation.py` file);
6: Draw parameters data from random variables (in `CC.mod` or `CM.mod` file);
7: Run the optimisation and export the resulting hospital costs;
8: Total annual cost variance meet an expected Confidence Interval?
. Yes: Go to step 9;
. No: Accumulate the resulting hospital cost and go to step 7;
9: Measure the hospital total cost statistics (in `costest.py` file);
10: Generate charts and the report of total cost estimation. Stop (in `graphics.py` file).

[a]† Configuration parameters are presented in Table 4.

We used SPSS to produce cost functions and Python (Python Language Reference, version 3.8.2, from the Python Software Foundation, https://www.python.org, Amsterdam, 1995) to implement the simulation-optimisation algorithm 1, data visualisation, and reports. The optimisation models were implemented and solved with GLPK [38] in an x64 Dell Intel i7 2.9GHz processor and 16GB RAM.

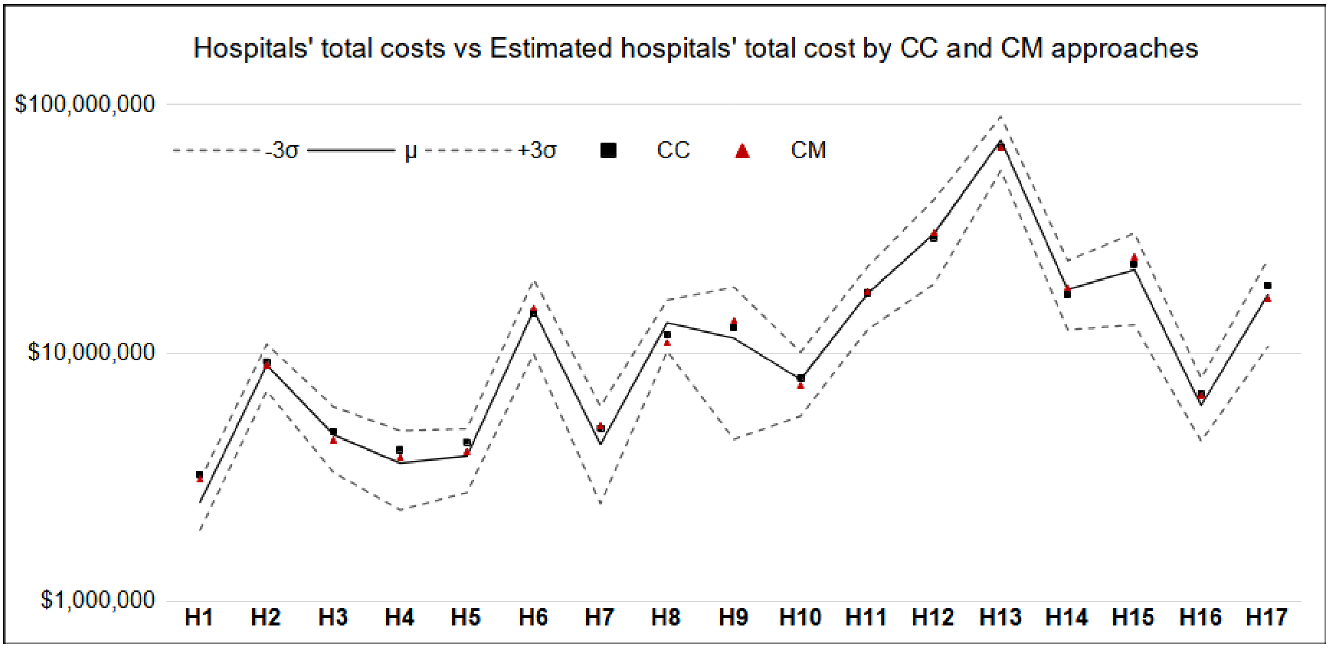
3. Results and discussion

3.1. The estimate of hospital costs

The results of CC and CM approaches correspond to estimates of 17 hospitals' total costs. We used the log scale in Figure 2 to enable the identification of hospitals of different sizes, types, and specialities. The μ in Figure 2 corresponds to the mean of hospitals' real cost considering ten years of recorded data. The estimates are close to the historical average annual costs and within the historical variation range.

The hospitals' total annual costs can be described for each approach, CC or CM, by selecting key parameters. The estimates are presented as mean ± 1.96 standard error (i.e., 95% of Confidence Interval) assuming the normality of the distribution. Let ε be the total of employees, η be the number of nurses, α be the number of administrative staff, θ be the number of general technicians, and ξ be the number of college-educated employees allocated to each hospital. Additionally, let π be the number of beds, and ψ be the number of medical imaging equipment. From a CC approach, a hospital would cost \$ 149,291 η ± 13,636 with employees, \$ 40,404 η ± 9,862 with third-party services, \$ 12,822 α ± 1,801 with medical goods, \$ 1,324 θ ± 206 with general expenses, \$ 429 ε ± 79 with depreciation, and \$ 9,943 η

Figure 2. The hospitals' real annual costs and CC and CM estimates.



± 1,987 with others. From a CM approach, we estimate that a hospital costs \$ 149,306 η ± 13,644 with employees, \$ 736 ε ± 44 with outpatient, \$ 39,658 η ± 13,498 with medical clinic, \$ 1.807 ε ± 90 with urgency and emergency, \$ 5,949 π ± 1,829 with surgical clinics, \$ 83,641 ψ ± 9,109 with adult ICUs, \$ 120,766 ψ ± 9,744 with paediatric ICUs, \$ 295 ε ± 14 with maternity, \$ 513 ε ± 16 with neonatal ICUs, and \$ 1,325 ξ ± 191 with others.

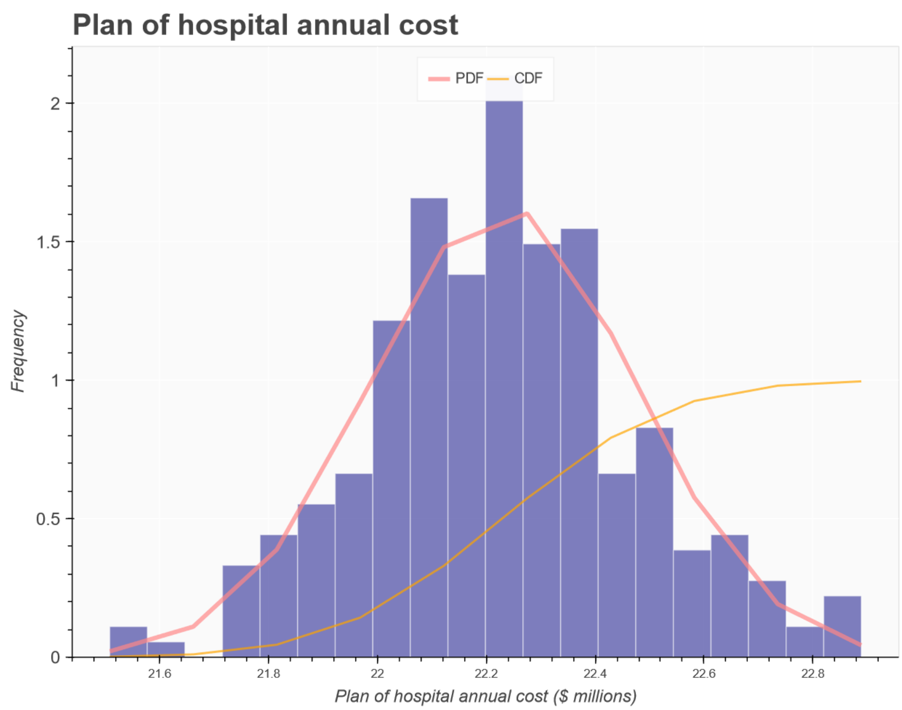
The hospital cost estimate of each approach is the basic scenario. For planning future costs, the health care planner can conveniently set the parameters as investment values, new medical equipment, expansion, reserve for contingency, or salary adjustments and use the simulation-based optimisation approach.

3.2. *The plan of hospital costs*

We now set the parameters for planning hospital costs in the simulation-based optimisation approach. Some parameters, such as the number of employees, or beds, are readily known. However, some data, such as salary or category distribution, are not available for every hospital. We used the National Register of Health Establishments [39] and the Brazilian Classification of Occupations database [40] as the reference to set the average distribution of employees by category, and the average salary per category in the hospital sector, respectively. We adjusted the values annually according to the cumulative inflation provided by the Central Bank. Brazil presents 6,814 hospitals which 2,644 are public. The resulting classification of all Brazilian hospitals by size (number of beds), number of employees, employees per bed, and the distribution of employees by category for Brazilian general hospitals, for instance, are shown in Tables A2 and A3 of the Appendix A. The resulting data fill the parameters described in Table 4.

Figure 3 illustrates the model results for the hospital H15 by a CC and CM approach. The results from the simulation-based optimisation approach show a probability density function and a cumulative probability function. The mean

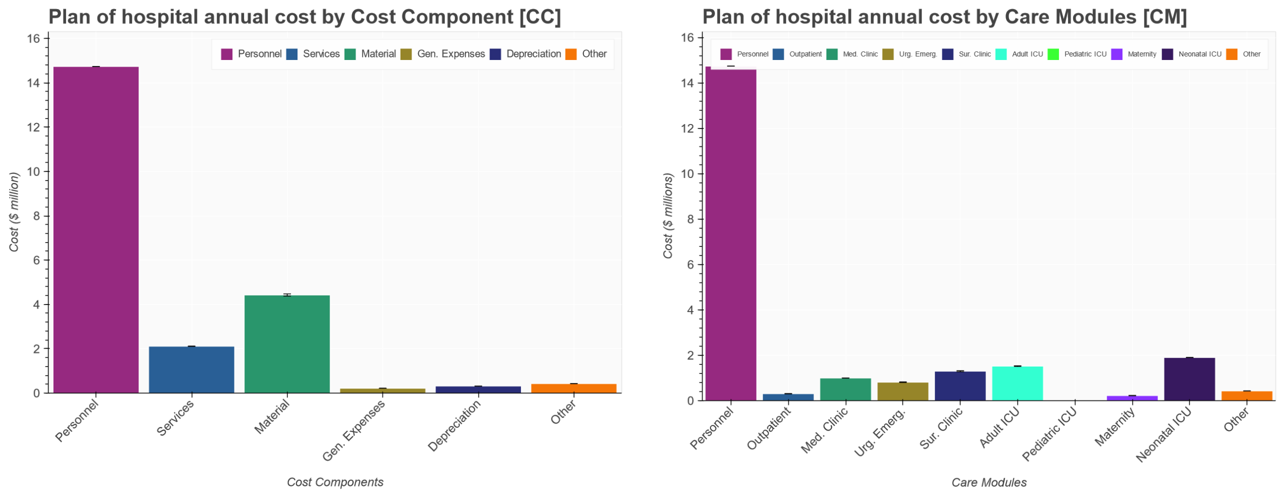
Figure 3. The hospital's annual cost plan considers both CC and CM approaches. The evaluation of total cost occurs by reconciling data from both simulations into a single distribution (this hospital has no Paediatric ICU).



hospital annual cost is \$ 22.23 ± 0.06 million (CI 95%), the standard deviation is \$ 0.24 million, the median is \$ 22.23 million, between the minimum value of \$ 21.51 million and maximum value of \$ 22.89 million. The hospital costs were assigned to different cost blocks, CC and CM, according to each strategy. Thus, it is natural that small discrepancies between the two results may occur. Therefore, we reconciled the total cost from each approach into a single distribution to aid decision-makers in analysing results. Figure 4 presents the details of CC and CM values. Thus, both results can better support decision-making if compared to a single approach providing valuable information about the macro-structure of cost division and of productive cost centres by type of service.

Figure 4(a) shows the personnel, third-party services, medical goods, general expenses, depreciation, and other costs. The sum of such values is equivalent to the hospital's annual cost under the CC approach. Figure 4(b) shows the CM costs, represented by personnel, outpatient, medical clinic, urgency and emergency, surgical clinic, adult ICU, paediatric ICU, and others, which is equivalent to the hospital's annual cost by the CM approach. The algorithm also generates a plan of the expected wage costs with staff per category. The resulting plans of CC and CM for all hospitals are available in supplemental material.

Our findings reproduce the published theory [41], with personnel costs representing approximately 69% of the total expenses. Nurses and their support, general technician, represent the significant single-cost elements, as seen in [36]. Through the CC approach, the costs of medical goods and third-party services represent up to 27% of the total cost, as seen in the literature [16]. The values of general expenses, depreciation, and others add up to 4% of the total annual cost of the hospital. The CM approach reveals that, after personnel costs, the urgency and emergency, medical clinic, and outpatient costs add up to 18% of the total cost. The values of adult ICU, paediatric ICU, and others add



(a) Cost components.

(b) Care modules.

Figure 4. Plan of hospital annual costs for each approach CC and CM.

up to 13% of the hospital's total expenses.

Dimensioning hospital requirements and population needs are not within the scope of this work. However, with a cost-projection tool in hand, we can set the model parameters considering future hospital decisions. Therefore, we evaluate two additional illustrative scenarios considering a divestment program and an investment plan with new professionals and infrastructure expansion. In a **divestment scenario**, the hospital directors plan to close five ICU units (15 to 10), remove three diagnostic equipment (13 to 10) and dismiss 129 employees (729 to 500). Of those, 28 are higher-level employees (108 to 80), and 14 are nurses (74 to 60). The reduction of employees would reduce the capacity to admit patients in ICU units (577 to 300), outpatient care (9724 to 8000) and admissions for hospitalisation (3500 to 3000), affecting hospital production (124827 to 104000). In an **investment scenario**, the hospital directors plan to hire 71 employees. Of those, 26 are nurses, and four are higher-level employees. The plan also includes the salary adjustment of 5% to all professionals, the expansion of UTI capacity with two new ICU units (15 to 17), the purchase of three diagnostic equipment (13 to 15), and two new CT Scanners. There is also a plan to invest \$300,000 in the purchase of computers and administrative equipment, \$100,000 in medical supplies, and \$600,000 in medical equipment. The hiring of new employees and equipment would increase the capacity to admit patients in ICU units (577 to 800), outpatient care (9724 to 11000) and admissions for hospitalisation (3500 to 4000), also affecting hospital production (124827 to 144000). Table 5 shows the simulation-based optimisation results after setting the parameters for each scenario.

Table 5. The proposed model enables designing global budget scenarios according to the hospitals' plans.

Hospital	Annual cost estimate	Plan description	Delta (Δ)	Global budget
		Divestment	-\$5.47 million	\$16.76 $\pm$ 0.69 million
H15	\$22.23 million $\pm$ 0.72 million	Maintenance		\$22.23 $\pm$ 0.72 million
		Investment	+\$18.66 million	\$40.89 $\pm$ 1.17 million

Brazilian public hospitals are part of a broader health care infrastructure called the Unified Health System (see

[42, 43, 44] for a comprehensive description). Funding policies also consider public and private (not-for-profit) services that occur in primary (basic) care, secondary (specialised) care, and hospitals. Although Brazil spends around 9.5% of the GDP on health care, 60% of this expenditure is private, leaving the Unified Health System under-financed, resulting in marked health inequalities [44]. In the LMIC's health care, the situation is similar. The competition for funding between the public and private sectors has redirected public funds and personnel to private sector development, yielding reductions in public sector service budgets and staff. Therefore, the public health services have experienced more limited availability of equipment, medications, and trained healthcare workers [45]. A comparative study in LMIC showed that the private sector is *not* more efficient, accountable, or medically effective than the public healthcare systems [45]. There is also an appeal to using a global budget as a policy tool to reduce public hospital expenditure by cutting inefficient costs. However, in the countries of OECD and China, the effectiveness of a global budget as a cost-containment tool has varied enormously [46, 47]. In France, for instance, a global budget policy implementation in public hospitals aimed to downsize expenditures by removing inefficiencies and, consequently, reducing costs. It did result in expenditure reduction, but from the service volume decrease, while the services' relative values remained constant [48]. Therefore, this work does not propose a hospital global budget procedure as a cost-containment tool but a method to aid health managers in hospitals' global budgeting and policymakers in improving fairness in public hospitals' financing.

4. Conclusion

The central purpose of this study has been to estimate and plan the total costs of public hospital units, which are essential facilities in the health care network. The use of CC, describing the macro-structure of cost division in standardised reports, and of CM, representing the grouping of productive cost centres by type of service, produced key parameters to estimate hospitals' annual cost. The simulation-based optimisation used the CC and CM cost functions for hospitals' global budgeting. The approach contributed to filling a literature gap due to the scarcity of integrated methods for estimating and planning hospitals' annual costs. The study used cost data from 17 public hospitals' databases.

The main findings of our analysis were consistent with our hypothesis. In the lack of detailed operational and financial data, hospitals of different sizes and characteristics can have their costs estimated and planned in a budgeting task adopting the proposed simulation-based optimisation approach. By the CC modelling strategy, the hospitals showed a stable proportional costs division. Personnel, third-party services, and medical goods represented more than 90% of the hospitals' costs. The CM approach revealed that, after the personnel cost module, the additional modules are proportional to the size of the hospital. However, the hospital's characteristics used in the study are not considered conclusive due to the small sample size.

This work presents some limitations. Our model is implicitly multi-objective, with objectives in different dimensions. We chose a *a priori* choice of weights in a goal programming technique to reduce the optimisation computation cost since the simulation-based optimisation requires numerous simulation rounds. Therefore, developing an explicitly multi-objective approach within a simulation-based optimisation framework and efficiently solving the problem remains a challenge. This strategy provides a Pareto front, enabling *a posteriori* the articulation of preferences. Additionally, the samples of 2,400 records represent ten years of historical data from 17 public hospitals that provide different services. However, the approach can not be applied to any arbitrary hospital. The CM of Neonatal ICUs and Paediatrics ICUs, for instance, are less frequent (some of the R^2 values of Table 3 are very low). Therefore, some accounting and operations data of more diverse sample strata may be required to re-fit the coefficients and improve the description of the hospitals' costs. Consequently, we suggest efforts in the direction of increasing the number and heterogeneity of participant hospitals.

The paper proposed a flexible simulation-based optimisation algorithm that integrates the estimating and planning of hospital costs considering historical data from a sample of hospitals with different sizes and characteristics. The estimates allowed us to draw inferences about hospitals' annual costs. However, we did not evaluate how much a hospital *should* cost nor the impact of new technologies, such as telehealth [49], on hospitals' costs. Therefore, future research can explore the efficiency and effectiveness metrics, location, and hierarchy influence on hospitals' budgeting since hospital funding should not be considered in isolation from the health care system.

Data availability statement: The data that support the findings of this study are openly available in the four repositories and URLs below.

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A. List and description of data set features

In this section, features used in this study are paired with their respective meaningful descriptions. They are shown in different tables mentioned in section 2 subsection "Estimating hospital costs" of the manuscript.

Table A1. Hospital cost drivers used for regression and factor analysis

Variable	Description
qt_exist	Total Number Of Beds
qt_exist_cir	Number Of Beds Per Clinic (Surgical)
qt_exist_clin	Number Of Beds Per Clinic (Clinics)
qt_exist_obst	Number Of Beds Per Clinic (Obstetrics)
qt_exist_neonat	Number Of Beds (Neonatal)
qt_exist_ped_clin	Number Of Beds Per Clinic (Other Specialties)
qt_exist_hdia	Number Of Beds (Day Hospital)
qt_exist_uti	Number Of Beds (Icu)
qt_exist_uti_adulto	Number Of Beds (Adult Icu)
qt_exist_uti_neo	Number Of Beds (Neonatal Icu)
qt_exist_uti_ped	Number Of Beds (Pediatric Icu)
qt_exist_uci	Number Of Beds (Utsi)
qt_exist_uti_coronariana	Number Of Beds (Coronary Unit)
qt_manutencao_vida	Number Of Life Support Equipment
qt_diag_imagem	Number Of Diagnostic Imaging Equipment
qt_metodos_graficos	Number Of Equipment By Graphic Methods
qt_outros	Number Of Equipment - Others
qt_tomografos_comp	Number Of Ct Scanners
qt_ressonancia_magnetica	Number Of Mri Machines
qt_prof_nivel_superior	Number Of Employees With Higher-Level Occupations
qt_prof_nivel_tecnico	Number Of Employees With Auxiliary Technical-Level Occupations
qt_prof_enfermeiros	Number Of Nurses
qt_prof_aux_enfermagem	Number Of Nursing Assistants
qt_prof_tec_enfermagem	Number Of Nursing Technicians
qt_consultas_urg_amb	Number Of Emergency Consultations (Hospital Outpatient)
qt_demais_atendimentos_amb	Other Services (Outpatient)
qt_alta_complex_amb	Qt_Outpatient Production (High Complexity)
qt_media_complex_amb	Qt_Outpatient Production (Medium Complexity)
qt_total_amb	Total Outpatient Production
qt_sih_atend_eletivo	Sum Of Attendances (Emergency Category _ Elective)
qt_sih_atend_urgencia	Sum Of Calls In The Emergency Category
qt_proc_cli	Number Of Hospitalizations By Clinical Procedure Groups
qt_perm_cli	Days Of Stay Per Clinical Procedure Groups
qt_proc_cir	Number Of Hospitalizations By Groups Of Surgical Procedures
qt_perm_cir	Days Of Stay By Groups Of Surgical Procedures
qt_proc_outr	Number Of Hospitalizations By Groups Of Remaining Procedures
qt_perm_outr	Stay Days Per Remaining Procedure Groups

Table A1 continued from previous page

qt_parto_normal	Number Of Normal Deliveries Performed
qt_parto_cesaria	Number Of Cesareans Performed
qt_parto_total	Number Of Hospitalization Authorization (Obstetrics)
qt_perm_obstetrico	Total Stay (Obstetrics)
qt_obst_risco_habit	Number Of Hospitalization Authorization (Habitual Risk)
perm_obst_risco_habit	Total Stay (Habitual Risk)
qt_obst_alto_risco	Qt_Hospitalization Authorization (High Risk)
perm_obst_alto_risco	Total Stay (High Risk)
qt_parto_normal_alto_risco	Number Of High-Risk Normal Births
qt_parto_cesaria_alto_risco	Number Of High-Risk Cesareans
qt_perm_uti_adulto	Days Of Stay (Adult Icu)
qt_perm_uti_pediatrico	Days Of Stay (Pediatric Icu)
qt_perm_uti_neonatal	Days Of Stay (Neonatal Icu)
qt_perm_uci_adulto	Days Of Stay (Adult Utsi)
qt_perm_uci_pediatrico	Stay Days (Pediatric Utsi)
qt_perm_uci_neonatal	Days Of Stay (Neonatal Utsi)
qt_aih_sem_longa	Amount Of General Hospitalization Authorization (Except Long Stay)
qt_perm_sem_longa	General Total Stay (Except Long Stay)
qt_aih_longa	Number Of Hospitalization Authorization (Long Stay)
qt_perm_longa	Total Stay (Long Stay)
qt_proc_cli_longa	Number Of Hospitalization Authorization (Long-Stay Clinics)
qt_perm_cli_longa	Total Stay (Clinics With Long Stay)
qt_proc_cir_longa	Number Of Hospitalization Authorization (Surgical With Long Stays)
qt_perm_cir_longa	Total Stay (Surgical With Long Stay)
qt_aih_media_complex	Qt_Hospital Production (Medium Complexity)
qt_perm_media_complex	Total Stay (Medium Complexity Hospitalizations)
qt_perm_uti_media_complex	Total Icu Days (Medium Complexity Hospitalizations)
qt_aih_alta_complex	Qt_Hospital Production (High Complexity)
qt_perm_alta_complex	Total Stay (High Complexity Hospitalizations)
qt_perm_uti_alta_complex	Total Icu Days (High Complexity Hospitalizations)
qt_diarias_uti_total	Number Of Days In The Icu (Icu_Mes)
media_dias_uti_total	Average Number Of Days In The Icu
qt_diarias_uci_total	Days Of Stay (Utsi)
qt_proc_total	Total Hospital Production
qt_perm_total	Days Of Stay (General)
sum_production	Total Production (Outpatient + Hospital)
qt_aih_uti_adulto	Number Of Hospitalization Authorization (Adult ICU)
qt_aih_uti_neo	Number Of Hospitalization Authorization (Neonatal ICU)

Table A2. Classification of Brazilian hospitals' size by the number of beds

Classes (Beds)	Hospitals (1)	Employees (2)	Beds (3)	(2)/(3)
– - 25	2,521	81,115	32,374	2.5
26 - 50	1,754	111,886	65,181	1.7
51 - 100	1,279	199,965	89,993	2.2
101 - 200	854	348,723	118,282	2.9
201 - 300	265	218,890	63,895	3.4
301 - 400	84	107,528	28,349	3.8
401 - 500	27	48,030	12,080	4
501 - 600	12	29,933	6,661	4.5
601 - 700	5	21,098	3,164	6.7
701 - 800	1	5,300	726	7.3
801 - 900	5	18,377	4,225	4.3
901 - 1000	3	13,947	2,908	4.8
1,001 - 1,100	2	13,185	2,157	6.1
1,101 - 1,200	1	5,123	1,177	4.4
1,201 - More	1	11,984	1,543	7.8
Total	6,814	1,235,084	432,715	2.9

Table A3. Distribution of positions by function for general hospitals

AREA	POSITION	FREQUENCY ABSOLUTE	FREQUENCY RELATIVE
Administrative	Director	7,376	0.31
	Manager	3,655	0.62
	Coordinator	4,931	0.42
	Advisory	33,078	2.79
	Analyst	1,766	0.15
	Engineer	610	0.05
	Technician	7,911	0.67
	Other Admin	90,423	7.95
Operations	Social worker	8,348	0.7
	Bio medic	5,499	0.46
	Dental Surgeon	8,530	0.72
	Nurse	122,618	10.34
	Pharmaceutical	17,600	1.48
	Physicist	341	0.03
	Physiotherapist	24,736	2.08
	Speech Therapist	4,191	0.35
	Nutritionist	10,584	0.89
	Pedagogue	149	0.01
	Physical Education	214	0.02
	Psychologist	7,956	0.67
	General technician	445,703	37.57
	Occupational Therapist	1,469	0.12
	Other Social	48,746	4.32
Medical	Doctor	323,549	27.27
Total		1,186,383	100