Are Portuguese hospitals suitably clustered according to their activity, quality, access, and expenses? An exploratory analysis on behalf of financial sustainability

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Dedicado aos meus avós Luzia e Serafim
a quem tanto devo

Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Preface

The work presented in this thesis was performed at the INESC-ID, during the period of January-December 2020, under the supervision of Prof. Diogo Ferreira, Prof. Rui Henriques and Prof. Alexandre Nunes from the ISCP.

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Resumo

A sustentabilidade financeira tem sido um dos maiores desafios do sistema de saúde português. Portugal adaptou diversas estratégias para promover a eficiência na saúde. A aplicação de um preço unitário único das consultas externas, definido para cada grupo hospitalar, correspondendo ao custo mínimo identificado para este serviço em cada classe de hospitais do Serviço Nacional de Saúde, constitui um exemplo na implementação de medidas que estimulam o aumento da eficiência. O agrupamento destas unidades foi gerado pela metodologia de clustering, utilizando-se as variáveis que explicavam os custos de atividade. No entanto, desconhece-se a adequação deste modelo à realidade atual, uma vez que não foram efetuados ajustes após a sua implementação em 2013. Verificamos que quatro unidades de saúde não integram a categoria mais adequada. Além disso, das 20 metodologias de clustering testadas, a silhueta máxima obtida foi de 0,36, indicando que os hospitais estudados são muito heterogéneos. Deste modo, levantam-se dúvidas quanto à sua implementação para financiamento e benchmarking. Os nossos resultados demonstram ser necessária uma revisão do processo de agrupamento, sendo que este procedimento deve passar a abranger também as dimensões ambiental, de qualidade e acesso aos serviços de saúde, uma vez que no cenário mais recente melhores resultados são obtidos com a sua incorporação. Estas recomendadas são fundamentação para a garantia de um financiamento e avaliação justa dos prestadores. Estima-se que, devido à categorização inadequado, os prestadores recebem anualmente menos de € 59 milhões a € 110 milhões do que o montante devido relativo ao serviço prestado.

Palavras-chave: Hospitais, agrupamento, financiamento, benchmarking, Sistema de saúde português

Abstract

Financial sustainability has been one of the major challenges faced by healthcare systems. Portugal adopted strategies to promote efficiency in healthcare. One strategy implied the application of the lowest price for the consultations activity found in each of subsets of hospitals belonging to the National Health Service, thus promoting the providers' search for efficiency. This grouping was generated by clustering methodology to the data variables that could explain the costs of their activity. However, the adequacy of the established model concerning the present reality of the hospitals is unknown, as no adjustments have been implemented proceeding its initial application in 2013. Here we show that the current classes do not adequately reflect the current reality of the units. We found that four healthcare units do not integrate the most suitable category. Furthermore, from the 20 tested clustering methodologies, the maximum achieved silhouette is 0.36, indicating that the providers are the healthcare providers are not well grouped. In this context, doubts concerning its implementation for funding and benchmarking can be raised. Our results demonstrate that a revision of the clustering process is necessary. Additionally, this procedure should also encompass variables covering environmental, quality and access of the healthcare services dimensions, since for the present scenario the best results are obtained when these criteria are incorporated. These recommend steps are critical to ensure that the funding and benchmarking are fair, and to avoid the underfunding of the institutions. It is estimated that, due to inadequate grouping, providers receive yearly less €59 million to €110 million than the due amount.

Keywords: Hospitals, Clustering, Funding, Benchmarking, Portuguese healthcare system

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Abreviations

ACSS Central Administration of the Health System

CDTT Complementary and Diagnostic Tests and Therapies

CH Hospital Center

CHAA Centro Hospitalar Alto Ave

CMI Case Mix Index

DBSCAN Density-Based Spatial Clustering of Applications with Noise

DEA Data Envelopment Analysis

DRG Diagnostic Related Group

GDP Gross Domestic Product

H Hospital

HS Healthcare System

HSJF Hospital de São José - Fafe

INE National Statistics Office

LHU Local Health Unit

MH Ministry of Health

NHS National Health Service

NN Nearest-Neighbour

OECD Organisation for Economic Co-operation and Development

PCA Principal component analysis

PPP Public-Private-Partnership

RHA Regional Health Administrations

RN Referral Network

SPA Public Administrative Sector

SUB *Serviço de Urgência Básica*

SUMC *Serviço de Urgência Médico-Cirúrgica*

SUP *Serviço de Urgência Polivalente*

WCSS Within-Cluster Sum of Squares

WHO World Health Organization

Chapter 1

Introduction

1.1 Motivation

The National Health Service (NHS) is the main provider of the healthcare services in Portugal. The NHS is funded mainly by taxes and it ensures universal care access to all residents in Portugal, regardless of social, economical, and legal status (Simões et al., 2017). The NHS was responsible for 57.2% of the total health expenses in Portugal in 2018. This amounts to more than €10 000 million.[1] The hospitals receive the majority of the financial resources allocated to the NHS (Ferreira et al., 2020). In 2020, around €5 200 million were designated to the NHS hospitals (ACSS, 2019). This value does not include the additional financial reinforcement defined in July of 2020, as a consequence of the pandemic of COVID-19 that the world is still facing.[2]

The hospitals that belong to the NHS are divided into groups, which are used for benchmarking and funding. The current grouping was implemented for the first time in 2013 up to nowadays (ACSS, 2012). This segregation of the units was performed by applying a clustering methodology to a data set that characterised the hospitals according to the installed capacity and production of healthcare services, variables which are able to explain the costs of the providers. [3]

The pertinence of an exploratory analysis conducted in this master dissertation for grouping the Portuguese public hospitals is supported by two major reasons. The first is the time that has passed since the definition of the established groups. And the second concerns the dimensions considered in the process of segmenting hospitals into classes.

Firstly, the presentation of the prevailing model occurred in 2011. One of the arguments put forward for supporting the employment of the proposed hospital grouping was that the previous financing scheme did not reflect the contemporary reality of the institutions. Eight years have passed since the last funding model was instituted (in 2003) and significant transformations occurred in the contemplated hospitals (Candoso et al., 2011). Within this framework, it is relevant to assess the suitability of the current model against the present reality of the providers, because it has already the same number of years since the

[1] Instituto Nacional de Estatística - Estatísticas da Saúde : 2018. Lisboa : INE, 2020. Available at `https://www.ine.pt/xurl/pub/257793024` accessed on 18/11/2020

[2] `https://data.dre.pt/eli/lei/27-A/2020/07/24/p/dre` accessed on 07/11/2020

[3] `https://benchmarking-acss.min-saude.pt/BH_Enquadramento/AbordagemMetodologica` acessed on 03/02/2020

conception of the current model. Additionally, the document that sets the incorporation of the grouping into the funding schemes for the publicly managed hospitals acknowledges the existence of providers that were in frontier zones between two groups (ACSS, 2012). Wherefore slight variations along the years may have placed these units in different groups.

Secondly, the process that led to the established grouping utilized variables which explained the costs of providers (ACSS, 2012; Nunes, 2020). Nevertheless, this approach does not take into account the access and quality of the services that were provided, neither the environment dimensions that have an impact on the activity and performance of healthcare providers. These dimensions (access, quality and environment) are essential so that fair comparisons can be made (Ferreira et al., 2019).

As a result of the aforementioned challenges, new work is necessary to understand the impact that the hospital grouping has on the benchmark of these providers and on the funding attributed to these institutions. Hence it is fundamental that the division in groups reflects the reality of the institutions, as an essential requirement for ensuring a fair funding and benchmarking can be performed.

1.2 Objectives

This work yields three objectives. The first is to construct the model that considering the information available replicates the currently established hospital groups. The second is to categorize the same healthcare providers into classes that generated from the application of the most recent data. The third consists on additionally incorporating the dimensions of access, quality and environmental in the process. This work contemplates three phases that correspond to each one of the goals.

The first phase of the work is structured and oriented to answer the following questions:

- In light of the available information (data and methods), is it possible to replicate the results obtained by Central Administration of the Health System (ACSS)? Which is the methodological procedure that produces the closest result?

- According to the data available, what is the result and method that produces the grouping that can best categorise the hospitals?

The second phase proposes to tackle the listed inquires:

- When the originally proposed methodology is applied to the most recent data available, do the results coincide with those from the model that uses the data contemporary to one that established the currently accept grouping?

- Respecting the current funding schemes and guidelines for public hospitals, what would be the difference in the funding of these units if different classes of providers are used?

- Which are the features that are determining the clusters distribution of the studied care providers?

The third and last phase aims at replying to the questions presented here:

- Following the same methodology and context but incorporation also the access, quality and environmental factors, do the clustering results match those obtained without these?
- When the same methodology is applied to the most recent data available do the results coincide with the results from model that uses information from some years ago to the model that established the currently accepted grouping? And what about the established groups?
- According to the available data, which clustering approach produces the grouping that can best separate groups of hospitals?
- Applying the current funding schemes for the public hospitals what would be the difference in the payments made to these units if alternative results are considered?
- What features define the conglomerations of the studied providers?

1.3 Contributions

The major contributions of this thesis are:

- Development of a dataset with public hospital, encompassing the acquisition, processing and consolidation of administrative data from multiple sources: ACSS, National Statistics Office (INE), Ministry of Health (MH) reports, which can be used for future research studies;
- Validate the adequacy of the groups of hospitals established in 2013 given the situation described by the most recent information made public;
- Exploring the clustering results of the NHS hospitals by expanding the amplitude of variables considered in the aggregation of these health units. In particular, by including notable parameters of quality, access and environmental factors, that were not taken into consideration in the process that culminated in the currently established categorization;
- Exploration of different strategies of the categorization of healthcare providers process regarding features selection and clustering methodology;
- Generating interpretable domain-based decision trees criteria of the aggregation of the units;
- Assess the financial impact on the funding of public hospitals considering some selected cases and scenarios against the current payment schemes.

1.4 Organization of the document

The document is organized in seven major parts. Chapter 2 introduces essential background on hospital funding and chapter 3 on the clustering process. Chapter 4 introduces the proposed methodology. Chapter 5 gathers the major results from the application of the proposed methodology onto the public hospitals. Chapter 6 provides a comprehensive discussion of the results in an attempt to answer the aforementioned research questions, and further highlights managerial and political impacts. Finally, chapter 7 presents the main concluding remarks and future directions are identified.

Chapter 2

Background: The Healthcare system

This chapter begins with Section 2.1 which introduces the global concepts of the healthcare system (HS) from which this dissertation is built upon. These notions are instantiated for the national system in the subsequent section, Section 2.2.

2.1 Healthcare system: A global perspective

According to World Health Organization (WHO) (2007), a HS *"consists of all organizations, people and actions whose primary intent is to promote, restore or maintain health. This includes efforts to influence determinants of health as well as more direct health-improving activities. A health system is therefore more than the pyramid of publicly owned facilities that deliver personal health services. It includes, for example, a mother caring for a sick child at home; private providers; behaviour change programmes; vector-control campaigns; health insurance organizations; occupational health and safety legislation. It includes inter-sectoral action by health staff, for example, encouraging the ministry of education to promote female education, a well known determinant of better health ".* It is a complex concept that encompasses national and regional subtleties.

As previously declared, the core mission of a HS is to advocate for health. This notion is defined by WHO as *"a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity"* (World Health Organization (WHO), 1948).

There are three major dimensions in a HS: *financing* the system with capital, whether it comes from taxes, social contribution or private funds, *providing healthcare* in a primary care centre, major hospitals or in a rehabilitation clinic, and also the *regulation* of all the players involved both in the financing and in the provision of care (Wendt et al., 2009).

Worldwide, HS are structured differently. Classification systems have been conceived enabling comparison of different models. We introduce one of the most recognized conceptual frameworks for HS, the model described in Wendt et al. (2009). This taxonomy system is established predicated on the principal players for the dimensions described in the preceding paragraph. Theoretically, there are twenty-seven different possibles combinations. Albeit, there are only six of these combinations found implemented in

HS of the countries of OECD (Organisation for Economic Co-operation and Development), which are showed in Table 2.1 (Böhm et al., 2013).

Table 2.1: Health System Types of OECD countries. Description of the actors responsible for the regulation, funding and provision of care. Adapted from Böhm et al. (2013)

Healthcare system type	Regulation	Funding	Provision	Cases
National Health Service	State	State	State	Portugal, Denmark, Finland, Iceland, Norway, Sweden, Spain, UK
National Health Insurance	State	State	Private	Australia, Canada, Ireland, New Zealand, Italy
Social-based mixed-type	Social	Social	State	Slovenia
Social Health Insurance	Social	Social	Private	Austria * , Germany, Luxembourg, Switzerland *
Private Health System	Private	Private	Private	USA
Etatist Social Health Insurance	State	Social	Private	Belgium, Estonia, France, Czech Republic, Hungary, Netherlands, Poland, Slovakia, Israel * †, Japan †, Korea *

Abbreviations: Reg - Regulation actors; Fund - Funding actors; Prov - Provision of Healthcare Services. Chile, Greece, Mexico, Turkey and Colombia weren't considered. The latter country wasn't included because it wasn't a member of the OECD at moment of this study OECD, and the remaining cases are related to absence of information;

* relative to most of the funding;

† just regarding majority in service provision.

Each HS develops its organization and activity to achieve the goals of accessibility, efficiency and quality of the healthcare (Jegers et al., 2002). The next paragraphs address the notions of these three vital aspects.

Access is the capability of the system to provide adequate healthcare services to citizens. It comprehends a multitude of factors: affordability of the care, the existence of the suitable infrastructure and service in a reachable distance, and the time to get serviced are suitable for the medical condition (Kerr and Hendrie, 2018).

Quality corresponds to the outcomes of the serviced offered, which is the product of all the interactions that the patient had in the health care unit or system. The contemporary notion has a wide perspective of the entire system and it is much more than just the avoidance of human mistake or negligence of care (Tello et al., 2020).

Efficiency consists of maximizing the outputs. The output for a HS is the state of health of the population covered. The increment of the health levels is achieved with the allocation of resources to the institutions that provide healthcare services. This concept incorporates three other: technical, allocative and productive efficiency, which correspond respectively to using the minimum resources for achieving a particular health outcome, distribution the finite resources in the way that promotes the maximum health outcomes for the entire community and the available resources what is the mechanism/approach that maximizes the outcome (Palmer and Torgerson, 1999).

2.2 The Portuguese healthcare system

This section encompasses three elements. Section 2.2.1 which clarifies the socio-political context amidst the creation of the contemporary healthcare system. It is proceeded by the outline of this actual HS in Section 2.2.2. Then, Section 2.2.3 describes the NHS, which constitutes the core of the HS in Portugal.

2.2.1 A short story

Societies and communities are shaped by history, culture, traditions and habits of their people. This diversity of factors impacts the social, political and economical systems in existence. And the healthcare one is not an exception (Lameire et al., 1999).

Portugal lived under a dictatorship for forty-one years in the XX century. The transition to the democratic system took place in 1974 with the Carnation Revolution. The country enacts this political shift in the most recent surges of democratization of the continent (Fernandes, 2012). Only in 1979, it was instated an universal health system. Before, the State had a limited intervention on the HS. The major actors in the system were: 1) *"misericóridas"*, historically relevant provider which managed the majority of the hospital units; 2) social and health insurances schemes that covered certain working classes, that were established with the first national security law in 1946;[1] 3) Public Health services; 4) public hospitals, mostly on the big urban centres; 5) private services, that served only the wealthier fringes of society. The evaluation of this system was poor, both in terms of access and of quality (Lima, 2015; Simões et al., 2017).

The transition to a democratic Welfare State induce structural modifications in Portuguese society. One of the most relevant transformations was the repositioning of the State concerning its invention in the principal dimensions of the HS. This new paradigm is reflected in the Constitution approved in 1976, in which the right of protection for all citizens of health granted in the 64th article. It assures the right to the protection in health with the formation of a universal, general and free NHS, and also establishes the State as the main regulator. It takes three more years, for the conception of the NHS to take place, in 1979, officially contemplated in the Law no. 56/79[2] (Lima, 2015).

The concepts of welfare states and healthcare systems are only fully developed in the XX century. Despite the major policies that identify these notions were previously implemented at the end of the precedent century in Germany in a process led by Chancellor Bismarck (Briggs, 1961). The flourishing of healthcare systems (infused in the construction of a welfare state) only fully materialize and spreads globally after World War II.

[1] Decree-Law no.45002 `https://dre.pt/web/guest/pesquisa/-/search/628294/details/normal?q=+Decreto-Lei+n.%C2%BA%2045002` accessed on 20/09/2020

[2] `https://dre.pt/home/-/dre/369864/details/maximized` accessed on 20/09/2020

2.2.2 Present

In our modern world, HS constitutes one of the core interventions of any Welfare State. The relevance of this system is evidenced by the proportion of the public resources devoted to it. The funding of HS and the social security system constitute the major expenses for the national governmental budgets (Moran, 2000). OECD countries spent on average 8.8% of their Gross Domestic Product (GDP) in health in 2019, and more than 70% of this expenditure was financed by public sources.[3] In this picture, Portugal devotes a higher proportion of the GDP towards health than the OECD average, 9.6%, although the component of public contribution in this expense is above the OECD average (66%). [4]

As depicted in Table 2.1, the Portuguese HS is categorized as a NHS. The State assumes the responsibilities of the major functions of the system (Freitas et al., 2012). Our national healthcare system is inspired on the model of Lord Beveridge, that was one of the protagonists in the creation and implementation of NHS in the UK in 1948 (Arah et al., 2003).

Despite the preponderance of the State in the HS, there are other actors involved in the financing and provision of care. In 2018, there existed 230 hospitals, from those 111 integrated the NHS and 119 enacted their activity independently of the public system (this number comprises also the units belonging to the social sector).[5] The expansion of social and private units in the last two decades is portrayed as the reaction of the population with insurances and/or financial resources to overcome the relatively slow response of the NHS to the request of consultations and surgeries (Simões et al., 2017).

The regulation is performed centrally in MH, specifically by the Health Regulatory agency. This organization is in charge of supervising the entire health sector.[6] Despite integrating the MH, it holds independence for the pursue of its mission. It audits all the healthcare providers concerning: the compliance with the legislation; access to healthcare; respect of the users rights; assure the quality and safety; transparency and compliance with the law by the economic relations and to ensure the competition in the sector (Simões et al., 2017).

According to Simões et al. (2017), of the total expenses in health in Portugal around 66% is accounted to the NHS through public expending, and 34% is from private sources. From this latter expenses, 80% correspond to out-of-pocket money, which involves expenses for dental care (not included in the NHS response), expenses in private providers and user-charges for the NHS. The remaining 20% regards health insurances contributions. There are a few schemes of health insurance: some are associated with the labour sector (the case of public servants); and private voluntary health insurance, which can be associate with benefits that private corporations offer to their employees or they can be purchase by the individuals/families (Simões et al., 2017).

2.2.3 Portuguese National Health Service: Organization and structure

The provision of care is categorised in three levels: primary, secondary and tertiary.

[3] `http://www.oecd.org/health/Public-funding-of-health-care-Brief-2020.pdf` accessed on 01/12/2020

[4] `https://stats.oecd.org/Index.aspx?DataSetCode=SHA` accessed on 01/12/2020

[5] INE - Hospitais por Localização geográfica `https://www.ine.pt/xportal/xmain?xpid=INE{&}xpgid=ine{_}indicadores{&}contecto=pi{&}indOcorrCod=0008101{&}selTab=tab0` accessed on 18/11/2020

[6] Decree-Law no. 126/2014 `https://data.dre.pt/eli/dec-lei/126/2014/08/22/p/dre/pt/html` accessed on 21/09/2020

The primary can be defined as *"the provision of integrated, accessible health care services by clinicians who are accountable for addressing a large majority of personal health care needs, developing a sustained partnership with patients, and practising in the context of family and community"* (Starfield et al., 2005). In some systems, including the Portuguese and English ones, this level of care also acts as gate-keeping for the more specialized care. This control is considered necessary in a scenario with a scarcity of resources. This mechanism not only contributes to the containment of costs but also promotes a more equitable care, by matching the services with the needs (Forrest, 2003).

The secondary care represents the specialized healthcare provided in Hospitals. The tertiary level of care is concentrate on long-term care (recovery and rehabilitation), and in Portugal, the Public response is organized under the National Network for Long-term Care. Although, here the funding and management of the network are under the State most of the capacity of this network is provided by the social sector, such as the *Misericórdias* (Simões et al., 2017).

The MH is the institution that coordinates the planning and organization of the NHS. However, the managing responsibility for the primary and secondary provision of care lays under the five Regional health Administrations (RHA), that cover Portugal mainland. Moreover, these organizations are accountable for strategically manage the population health (Ferreira et al., 2019; Simões et al., 2017). RHA is responsible for guaranteeing the access of healthcare services and also implementing the health policies for the population under its responsibility, the regulation and legal framework for these institutions.[7] These entities play a fundamental role in the negotiation and celebration of the contracts that define the production of healthcare hired for NHS with each provider. The duties of contractualization and payment are done in collaboration with ACSS (Simões et al., 2017).

In 2018, 111 hospitals constituted the secondary level of health care of NHS. [8] These healthcare units are generally classified under two perspectives: the set of services offered and their juridical status, which has implications on the management of this entities. Since the legal framework defines the rules that condition the funding and governance of the organization.

So, on one hand, applying the former criterion the hospital is designated as specialized or general. The general hospitals provide a range of internal medicine and surgeries services. Whereas the specialized organizations focus exclusively on their activity in one medical field, this allows for high differentiation of care. The existing specialized hospitals focus on oncology (the three Portuguese Institutes of Oncology), physical medicine and rehabilitation, psychiatry and mental health, Ophthalmology and obstetrics (ACSS, 2019).

On the other hand, the hospitals of the NHS are categorized into four groups: i. Hospitals of the Public Administrative Sector (SPA); ii. Hospital and hospital centres (CH) with corporate public entity status (EPE); iii. Local Health Units (ULS); iv. Hospitals PPP.

The hospitals SPA are a minority of public hospitals, in the present moment there are only five that fit in this class.[9] This typology is the most ancient one. This model was attributed to the secondary level

[7]Decree-Law no. 22/2012`https://data.dre.pt/eli/dec-lei/22/2012/01/30/p/dre/pt/html` accessed on 08/09/2020

[8]INE - Hospitais por Localização geográfica `https://www.ine.pt/xportal/xmain?xpid=INE{&}xpgid=ine{_}indicadores{&}contecto=pi{&}indOcorrCod=0008101{&}selTab=tab0` accessed on 18/11/2020

[9]`https://www.sns.gov.pt/institucional/entidades-de-saude/` accessed on 06/07/2020

providers amidst the formation of the NHS. These institutions have limited autonomy. Possessing only full control concerning the financial and human resources. They are under the fiscal supervision of the MH, which enforces its authority over the management of the unit (Ferreira and Marques, 2015).

The second typology was originally implemented in 2005. The conception of the EPE status is motivated by the ambition of overcoming the shortcomings identified in the oldest legal and administration framework, SPA. This transformation consisted on the adoption of a more corporative structure so that hospitals can better develop their activities. The transition began in 2002, with the an intermediate version in the form the of hospital enterprise (SA) framework, that lasted until 2005. From this date, the figure of hospital SA was replaced by EPE status (Ferreira and Marques, 2015). All the CH that exist are under this framework. The aggregation of providers into hospital centres was made to increase the efficiency of the care provided by hospitals that share a geographical area (Ferreira et al., 2020).

ULS contemplate the vertical integration of the primary and secondary levels of care. This aggregation is conducted to improve management results and promote higher integration and articulation of care, as it encloses the hospital(s) and primary care units of a certain region. These entities have also the juridical status of EPE.[10] Currently there are eight ULS, which cover in their direct influence 12% of the country's population. These providers obtained 16.9% of the budget for public hospitals, in 2019 (Brito Fernandes et al., 2020).

The last category contemplates the healthcare units of PPP. This formula was created as an attempt to control the raising of the public costs on hospital care. Solely four hospitals are under this legal and administrative framework. These healthcare providers began to operate between 2009 and 2012. This model implement in Portugal is designated as the wave model. It consists of two independent contracts: a 30-year contract for the building and maintenance of the infrastructure and a 10-year contract for the clinical management (Ferreira and Marques, 2020; Ferreira et al., 2020).

2.3 Hospital clusters for funding and benchmarking

Section 2.1 states that HS should focus on accessibility, efficiency and quality of care. Being paramount monitoring and assessing providers regarding these dimensions. This section details the framework utilized in these tasks.

As referred in Section 2.2.3, there is a multitude of healthcare units concerning the level of care, specialization degree, geographical location, population served, legal and managerial frameworks, etc. Ergo the comparison of providers should be frame considering the similarity of the units (Byrne et al., 2009). The structure considered by NHS to conduct the analysis is the division of the hospitals depicted in Table 2.2.

The classes of units illustrated in Table 2.2 were presented in the 12^{th} [Portuguese] national of health economics conference in October 2011 (Candoso et al., 2011). The variables regarded in the process of construction of the groups are medical working hours; nursing working hours; beds; offices for medical appointments; hospitalization episodes; medical equipment; operating rooms; urgency episodes;

[10] Decree-Law no. 207/99 `https://data.dre.pt/eli/dec-lei/207/1999/06/09/p/dre/pt/html` accessed on 06/07/2020

Table 2.2: NHS Hospitals, their corresponding abbreviation and category

Name of the Health Unit	Abbreviation	Group
CH Médio Ave	CHMA	
CH Póvoa do Varzim/Vila do Conde	CHPVC	
HD Figueira da Foz	HDFF	
H Santa Maria Maior	HSMM	B
CH Oeste	CHO	
ULS Nordeste	ULSN	
ULS Castelo Branco	ULSCB	
ULS Guarda	ULSG	
ULS Litoral Alentejano	ULSLA	
H Vila Franca de Xira PPP	HVFX	
CH Barreiro/Montijo	CHBM	
H Senhora da Oliveira	HSOG	
CHU Cova da Beira	CHUCB	
CH Leiria	CHL	
CH Setúbal	CHS	
CH Baixo Vouga	CHBV	
CH Entre Douro e Vouga	CHEDV	
CH Médio Tejo	CHMT	C
HD Santarém	HDS	
CH Tâmega e Sousa	CHTS	
CH Cascais PPP	CHC	
H Loures PPP	HL	
ULS Alto Minho	ULSAL	
ULS Matosinhos	ULSM	
ULS Baixo Alentejo	ULSBA	
ULS Norte Alentejo	ULSNA	
CH VN Gaia / Espinho	CHVNG	
H Espirito Santo	HESE	
H Garcia da Orta	HGO	
H Fernando da Fonseca	HPDFF	D
CH TM Alto Douro	CHTMAD	
CH Tondela – Viseu	CHTV	
CHU Algarve	CHUA	
H Braga	HB	
CH Lisboa Ocidental	CHLO	
CHU de Coimbra	CHUC	
CHU Lisboa Central	CHULC	E
CHU Lisboa Norte	CHULN	
CHU do Porto	CHUP	
CHU de São João	CHUSJ	
IPO Porto	IPOP	
IPO Lisboa	IPOL	F
IPO Coimbra	IPOC	

H - Hospital; CH - Hospital Center; CHU - University Hospital Center; IPO - Portuguese Oncology Institute;

equivalent patients; complementary and diagnostic tests and therapies (CDTT); the number of distinctive medical and surgical Diagnostic Related Groups (DRG); the number of medical appointments; the number of complex medical and surgical DRG; the number of specialities offering consultations with a high differentiation level; classification of hospitals according to their urgency service; the number of different types of CDTT with high differentiation level; beds in specialized units; classification regarding university teaching duties; the ratio of resident physicians from the total medical doctors (Nunes, 2020).

The methodology followed focus on the efficiency and production point of view. As visible in the set of 22 features listed in the previous paragraph. The selection of these factors was guided by the effect of these on the structure of costs of the hospitals (ACSS, 2012; Nunes, 2020).

In Portugal, the NHS utilizes the hospital groups for benchmarking. Benchmarking defines a *"structured framework for pursuing worthwhile goals in an organized way"*, which derives originally from the operational concept used in the Xerox as a tool for discovering the best practices across the entire organization to spread its application across other departments (Camp and Tweet, 1994). The performance of the healthcare providers is available to any citizen through an online platform at the responsibility of ACSS.[11] According to this platform there are three main objectives for monitoring, reporting and benchmarking hospitals: 1) comprehend the differences on economical and financial performance; 2) assess the potential of improvement of each unit; 3) identify the best practices. [12] To sum up, benchmarking aims increasing the economical and financial performance of hospitals while promoting better access and quality of care.

Benchmarking is widely implemented. WHO uses this approach for evaluating and promoting the quality of care in European hospitals (Organization et al., 2007). Likewise US State of Michigan (Zodet and Clark, 1996) and at a wider level IBM Watson annually ranks the best performing hospitals, health systems and 50 best Cardiovascular Hospitals of the USA (Chen et al., 1999). [13]

But grouping hospitals can serve more intentions than solely benchmarking. The Portuguese NHS is one of those cases in which this approach has implications in the definition of funding schemes for the healthcare units. As the calculation of the monetary value to be transferred to each public hospital takes into account the hospital groups. These implications are clarified in Section 2.4.3.

2.4 Public hospitals funding

This section covers four topics. Section 2.4.1 outlines the financing scheme of public hospitals. Section 2.4.2 introduces concepts relevant for the reimbursement schemes of the hospital activity. It is proceeded by Section 2.4.3 that details the agreement that establishes the activity of the hospitals EPE and the corresponding payment. Finally, Section 2.4.4 describes the influence of the access and quality of care on the funding of the mentioned entities.

2.4.1 Overall resources allocation scheme

The Portuguese NHS is predominately financed by general taxes. The funds allocated are fixed every year in the annual government budget. This budget is designed to cover the total NHS expenditure. Although in the last decade, the norm has been the expenses on health exceeds the approved amount. And the government, usually, close to the end of the year attribute more resources to the NHS, which is used to reduce the stock of debt that has accumulated until that moment (Simões et al., 2017).

The annual General State budget designates the distribution of the money that is estimated to be collected in taxes. This allocation is done according to all the ministries. On its turn, each ministry

[11] `https://benchmarking-acss.min-saude.pt` accessed on 28/08/2020
[12] `https://benchmarking-acss.min-saude.pt/BH_Enquadramento/Objetivos` accessed on 28/08/2020
[13] `https://www.ibm.com/watson-health/services/100-top-hospitals` accessed on 06/09/2020

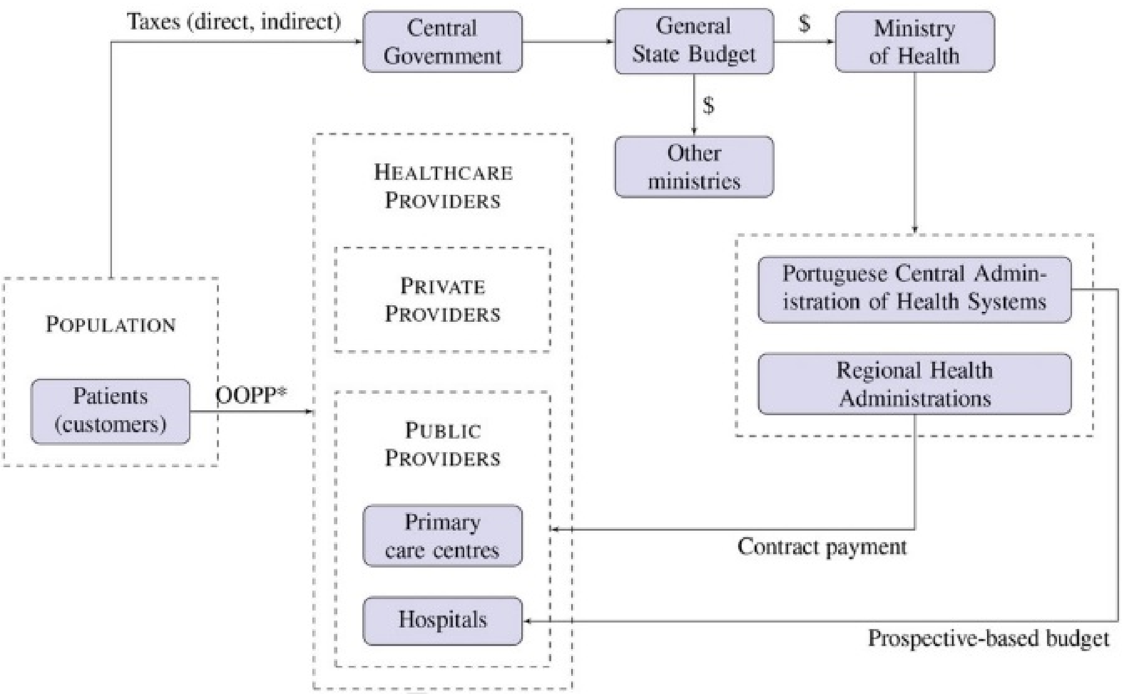

Figure 2.1: Financial scheme of Portuguese healthcare system. *OPP - out-of-pocket-payments. Source Ferreira et al. (2020)

allocates the attributed resources to the different missions that are accountable for. Figure 2.1 depicts the flow of financial resources in the HS. There are two sources of income for public hospitals. The most important comes from the General State budget, that is the path addressed in this work. While the other is obtained as out-of-pocket payments that the users incurred when acquiring particular services (Ferreira et al., 2020).

The financing scheme for the providers of secondary level of care is intricate due to the complexity and amplitude of the services. The Contract Program is the agreement between ACSS (in representation of the State) and the provider that discloses the funding attributed to the unit.

This contract is a prospective payment scheme. This typology of reimbursements consists of paying according to the estimated future demand for healthcare services. The allocation of resources for future estimated activity is based on Diagnostic Related Groups (DRGs), concept clarified in the subsequent Section. This approach is the tendency displayed by most OECD countries. The trend is justified by motivation that lead to the design of this financing model, which was overcoming the shortcomings of the antecedent model that was cost-based. The novel implement type promotes higher incentives for cost-control and efficiency (Miraldo et al., 2011).

2.4.2 Key concepts for the funding scheme

Three key elements for the funding schemes are equivalent/standard patient, DRG and Case Mix Index (CMI) (Freitas et al., 2012). These are discussed in the following paragraphs.

Firstly, equivalent or standard patient is defined in decree no. 839-A/2009. [14] It expresses the average user of the Public hospitals concerning the consumption of resources. This concept is involved in the computation of the value to be paid for the production on each activity line, since patients are compared with this reference in terms of costs.

The application of equivalent patient as a central piece in the process of funding raises few challenges. One is about the process of fairly translating the relation of singular medical case with the average patient scenario into a value. Given that not only there is an immense diversity of medical conditions, but also all the factors that impact the health outcomes. DRG emerged as a solution to deal with these concerns.

Since the 1980s, there is a consensus around DRG developed at Yale University by Fetter and Thompson (Fetter et al., 1980). This model is implemented in the majority of healthcare systems of Europe and North America (Mihailovic et al., 2016). Portugal introduced it in 1984, as a result of a collaboration between the MH and Yale University. Later on, in 1990, it approved the first pricing tables based on these concepts.[15] Also in that year, CMI was used for the first in the funding of the NHS (Urbano and Bentes, 1990).

DGRs are groups of patients similar clinically and in terms of the consumption of resources. Each DRG is also called class and is associated with a relative weight, which expresses the cost of this class compared with the national average episode of hospitalization. Besides the relative weight, other variables exist: primary diagnostic, age, gender, destination after discharge and weight after birth, the latter only applies to the newborn children. The reimbursement value and all the variables justed mentioned are depicted in decree no.132/2009 [16] and no.839-A/2009[17].

The encoding procedure of a hospitalization episode into the DRG class is described in Figure 2.2. Health providers record all medical and surgical procedures performed to the patient. Second, after the discharge of the unit, the medical record is analysed by a qualified physician that converts it into a series of codes that safeguards the information content. Finally, the codes obtained are processed by a computer algorithm that outputs the corresponding DRG class.

Since 2017, the clinical codification system in Portugal is based on the ICD version 10 Clinical Modification (ICD-10-CM). The ICD-10-PCS, PCS stands for Procedure Structure, is the analogous standard for medical and surgical procedures (ACSS, 2018). Figure 2.2 depicts the schemes that summarize the conversion process described above.

Price tables are set for DRGs classes. That is the reason for the encoding of the medical and surgical procedures into the DRGs. This process is done by complex algorithms. Currently, this role is attributed to the Grouper APR-31. APR stands for All Patient Refined (ACSS, 2018; Averill et al., 2003).

[14] http://www2.acss.min-saude.pt/Portals/0/C%C3%A1lculo%20do%20doente%20equivalente%20e%20ICM_2009_Finaln.pdf accessed on 22/08/2020

[15] Decree no.409/90 https://dre.pt/web/guest/pesquisa/-/search/574902/details/normal?q=portaria+n.%C2%BA409%2F90 accessed on 22/08/2020

[16] Decree no.132/2009 https://data.dre.pt/eli/port/132/2009/01/30/p/dre/pt/html accessed on 24/08/2020

[17] Decree no.839-A/2009 https://data.dre.pt/eli/port/839-a/2009/07/31/p/dre/pt/html accessed on 24/08/2020

[19] https://www.who.int/docs/default-source/health-financing/drg-q-a-guide-final-draft.pdf?sfvrsn\unhbox\voidb@x\bgroup\let\unhbox\voidb@x\setbox\@tempboxa\hbox{5\global\mathchardef\accent@spacefactor\spacefactor}\let\begingroup\endgroup\relax\let\ignorespaces\relax\accent225\egroup\spacefactor\accent@spacefactor4f64dad_1&download\unhbox\voidb@x\bgroup\let\unhbox\voidb@x\setbox\@tempboxa\hbox{t\global\mathchardef\accent@spacefactor\spacefactor}\let\begingroup\endgroup\relax\let\ignorespaces\relax\accent22t\

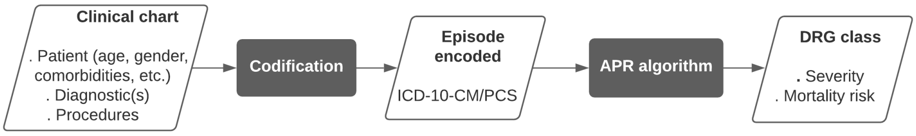

Figure 2.2: Scheme of the complete conversion process of a hospitalisation episode into a DRG class. Adapted from WHO Health financing guideline no.10 [19]

The aforementioned notions of equivalent patient and DRG are individual-centred, since they characterize single episodes. However, a hospital attends a highly diverge range of patient, being necessary a metric that captures the gross production profile, in terms of costs concerning the patients treated (Costa and Lopes, 2004). Presently, CMI is the notion in use for this task.

Equation 2.1 depicts the computation of CMI for a healthcare unit. Greater the value of CMI more a hospital attends patient who consumes more resources (Ferreira and Marques, 2016).

$$\text{CMI}_{\text{hospital x}} = \frac{\sum_i (\text{equivalent patients DRG}_\text{i})_\text{x} \times \text{weight DRG}_\text{i}}{\sum_i (\text{equivalent patients DRG}_\text{i})_\text{x}} \tag{2.1}$$

The actual funding scheme utilizes the value of CMI concerning the total hospitalization activity (including both surgical and medical procedures), ambulatory surgeries and medical services provided in ambulatory. The value associated with each subset expresses the average complexity of the patients covered by those sets. CMI assumes a positive value. If CMI $= 1$ then the typical profile of the users required the national average of resources to be properly served. Alternatively, in the scenarios of CMI < 1 the average patient attend presents medical conditions with lower complexity, thus generating lower costs. The other possibility is the provider being associated with CMI > 1, which causes the unit to require more resources than the average to adequately treat its users (Ferreira and Marques, 2016).

2.4.3 Contract Programs

As discussed in Section 2.2.3 there exist four juridical-administrative classes of hospitals comprising the network of secondary level of the NHS. This document solely covers the funding of hospitals which possess the statue of EPE. The funding is a complex process which is materialized in a few documents. From those, the contract program is held as the central piece. [20]The hospitals incorporate in ULS also share a few of the same mechanisms of the Hospitals EPE, although ULS are not included in the work. For information regarding the ULS funding is suggested the reading the latest terms of reference for contracting in 2020 (ACSS, 2019). Hospitals PPP have their own contracts formalized with the respective RHA. These agreements respect a different legal framework. For more information concerning this topic is recommended the reading of Ferreira and Marques (2020). Finally, SPA hospitals are financed directly from the annual State budget. [20]

The Contract program is the central document concerning the payment of the activity of hospitals EPE since 2002.[20] This commitment is celebrated between the RHA and each hospital. The document

egroup\spacefactor\accent@spacefactorrue accessed on 01/09/2020 stipulates the volume and type of the healthcare services that the provider will produce and the correspondent financial payment for those services. Each contract has a scope of a year (Simões et al., 2017).

This yearly agreement is integrated into a broader perspective, which encompasses triennial strategic planning. Hereby are listed the principal management instruments for the public hospitals: 1) Activities and budget plan (ABP) - *plano de atividades anual (PAO)* - applying for 3-years-period; 2) Management contract - *contrato de gestão* - in force during the mandate of the hospital administration; 3) Contract-Program - applying to the year that the contract refers to.

All the documents require the approval of the MH and the Ministry of Finance. The just listed documented are complemented with the presentation of the predictive annual Income Statement, a predictive balance sheet and a list measures quantified and calendared. All this to show that the financial situation is expected to converge to the reality signed on the ABP (ACSS, 2012, 2018; Ferreira et al., 2020).

The contract program is composed of mainly three sections: delivery of care, incentives and penalties. All the information conveyed in the following sections regards the contemporary funding schemes which are established in ACSS (2019).

2.4.3.A Delivery of care funding

The most important component of the funding concerns the billing of services hired. DRGs and CMI are used for computing the values for the major lines of activities, as formulated in Equation 2.2. It consists of predicting the number of standard patients that will be treated by that particular unit and them multiply it by the cost of the typical patient. This process is applied for all the different production lines under the categories of medical and surgical procedures performed. Including both the ambulatory and hospitalization activity. The vast majority of the billed activity are covered by this payment method.

$$\text{Budget for hospital} = \sum_{DRG} \text{N. of equivalent patients} \times \text{CMI} \times \text{Unitary price} \tag{2.2}$$

Further payment frameworks exist, these include the activity under the services of: 1) acute disease (ie. urgency activity, external consultations and home care); 2) specific health programmes (ie. programme for reduction of caesarean sections and programme for surgical treatment of obesity); 3) chronic or rare diseases (ie. HIV and Hepatitis C treatments); 4) reference centres (ie. for oncology and rare diseases); 5) integrated responsibility centres; and 6) palliative care. Section 2.4.4.A details one of these alternative reimbursements schemes - the billing of emergency services.

2.4.3.B Financial incentives

The incentives are incorporated in these reimbursement schemes to promote an increase in exigence levels and responsibility of the providers. Also, these stimuli are aimed to improve the activity performance and efficiency. Currently, there are two categories of incentives that the contract includes: 1) Institutional performance; 2) Relative performance - benchmarking.

[20] Decree-Law no.18/2017 `https://data.dre.pt/eli/dec-lei/18/2017/02/10/p/dre/pt/html` accessed on 30/08/2020

First, institutional performance incentive has a value of 5% of yearly funding for the institution. The attribution is conditioned to the compliance of the goals of agreed production and of efficiency in areas of activities that are considered a priority, at the national level and regional level, counting 60% and 40%, respectively.

The national component is divided into three topics: access, quality and efficiency. Each of these dimensions is assessed by selected indicators. The specialized units such as the oncological and psychiatry hospitals have slightly different metrics adapted to their activity, but share the main framework.

Second, the other regards the relative performance based on a benchmarking approach. This element began to be included in the contract programs of 2017. [21] It consists on the computation of the Index of Compared Performance, determined according to the achieved results in the set of indicators that evaluate access, quality and efficiency, resulting in an ordered list of providers per hospital category. The hospitals' classes that are utilized in this incentive are the grouping depicted in Table 2.2.

This incentive is awarded to the organizations that are placed first. The cost of this incentive is supported by all remaining units of the respective group. Therefore this incentive is a penalty for the institutions that have to finance the reward. The values of the award are not disclosed in the terms of contractualization.

2.4.3.C Financial penalties

The introduction of penalties in the contracts has two objectives: prevent non-systematic compliance of the contract by the institutions and to increment levels of demanding and rigour. The value of the sanction can not be higher than 3% of the global value of the contract-program of each hospital.

The application of penalties is determined by the computation of values of a set of indicators. In the case in which the hospital exceeds the interval of performance that is considered acceptable a sanction is applied.

The indicators assessed are categorized in five groups: programs of promotion and adequacy of access (36%); report and publication of information of management (10%); recording, consultation, sharing of information and digitization of processes (20%); billing of income and stocks (4%), and deviation of the financial results (30%).

2.4.4 How do the access and quality of the healthcare services are included in the funding process?

Access and quality performance are taken into account in solely tree elements of the contract program. These are: a) the line of production of urgency services (the variable component), b) the incentives, and c) penalties (ACSS, 2019). This section is dedicated to clarifying the impact on the total reimbursement value for the hospitals on each of those factors.

[21] `http://www.acss.min-saude.pt/wp-content/uploads/2016/10/Contratualizacao-Cuidados-SNS-Termos-Referencia_2017-VF.pdf` accessed on 25/09/2020

2.4.4.A Financial impact on the payment of emergency services

Factor a) is an element of the funding scheme of emergency services. This activity is categorized into three classes. The division concerns the set of medical specialities and respective differentiation level that an institution commits to offer in the emergency department. These typologies are *Serviço de Urgencência Básica* (SUB), *Serviço de Urgência Médico-Cirúrgica* (SUMC) and *Serviço de Urgência Polivalente* (SUP), listed in an increasing order of range and differentiation level of specialities provided. Naturally, the associated unitary price increments by the same order. These types are fully described in the decree no. 13427/2015. [22]

This activity is paid according to three components. The first is a fixed value that depends on the typology hired. The second is the marginal price, that is the value paid for each urgency episode, that surpasses the established production in the contract. The third is the variable component that depends on the performance of the unit. This last element corresponds to 5% of the fixed component.

2.4.4.B Financial impact on incentives and Penalties

The financial impact of the incentives and penalties ranges from the best scenario of adding 5% of the budget that is computed considering all the production lines to, the worst-case scenario, with the unit has to return to the value of 3% of the financial envelopment assigned. Also under the category of the incentives, it is to be included the impact of the result on the benchmarking incentive, described above in Section 2.4.3.C.

2.4.4.C Indicators used for assessing access and quality in the Contract Program

Hereby is summarised the fundamentals characteristics that health indicators must meet, according to Giraldes (2008). These are acceptability, feasibility, reliability, sensitivity to change and validity. The former refers to the (implied and explicit) agreement of all the people involved in the registry of the metric - patients and healthcare workers. The second aspect points to the need for ensuring that all the technical and practical requirements for the measuring, registry and process of the data are met. Reliability because the indicators are constructed to be applied to different providers with comparison purposes. Sensitivity is associated with the capacity of the indicator detect differences in the quality of the services. And finally, the latter characteristic is the validity of the methodology followed.

The set of indicators that are taking into account on the decision of attributing the institutional incentive are depicted in page 42 of the latest terms of reference for contracting in 2020 (ACSS, 2019). The same applies to the description of the metrics that evaluate the attribution of the relative performance incentive and the enforcement of the penalties in pages 45 and 46 of the specified document, respectively.

Additionally to the indicators that are outlined in the aforementioned tables, the activities focused in the present section (emergency services, incentives and penalties) take into account the efficiency. This latter element has an overwhelming prominence throughout the funding process. This section was

[22] Decree no. 13427/2015 `https://dre.pt/home/-/dre/71066231/details/maximized` accessed on 25/08/2020

written with the purpose to underline the lack of representation and consideration for the other two. Hence in this part of the document efficiency indicators are not addressed.

Access to adequate services has a higher importance in the funding schemes when compared to the quality indicators. It is also relevant that within each of these factors there are different metrics that can and are used to assess the performance on these areas. Its choice influences the behaviour of the providers.

2.5 State of the art on reimbursement of healthcare services

In this chapter so far it was outlined the funding paradigm of the Portuguese public hospitals. The work of this dissertation is built upon it, as it attempts not to structurally changed it, but improve the established model. Therefore, considering the topic it is relevant to the description of the state of the art on reimbursement of healthcare services.

Firstly, it is paramount to begin by addressing the sources of the financial resources in the HS. There exist two major possibilities: public sources (through taxation) and/or private. The latter encompasses out-of-pocket (funds directly paid by the user of the healthcare services) and insurances (indirectly paid by the user, which cover totally or partially health expenses) (Böhm et al., 2013).

Secondly, Jegers et al. (2002) proposes a comprehensive framework for comparing and classifying the several funding schemes available for healthcare providers. The system developed classifies the reimbursements schemes under three criteria: 1) variability of the unitary prices; 2) temporal relation between the provision of healthcare service and the respective reimbursement; 3) the element consider for the definition of prices. Regarding the former parameter, the schemes are categorized into static models or dynamic in respect to the evolution of unit price is permitted or not, respectively. The subsequent element divides the strategies into retrospective or perspective payment schemes, depending on the reimbursement proceeds or precedes the activity billed. The last criterion classifies in five subsets according to the factor that established the units for the scheme: a) item-of-service; b) patient-day; c) case; d) enrolled patient; e) period of time. Furthermore, the focus of incentives on a micro or macro perspective influence the typology.

Thirdly, the framework developed in Jegers et al. (2002) analyses the influence of the different schemes onto the access, quality and efficiency of the healthcare services. Due to the importance of these dimensions, studies were conducted in the recent years to identify the methodologies that ensure the highest performances regarding the access (Kerr and Hendrie, 2018), quality (Mathes et al., 2019) and efficiency (Cantor and Poh, 2018).

Fourthly, on one hand, it is vital to comprehend the practices and funding schemes that lead to the best results concerning all the dimensions aforementioned. On the other hand, it is equally important understanding the consequences of pursuing improvements for those elements produce on the other two. A rigours process should cover all the multiple connections (back and forward) between the pairs of factors. Understanding the implication of efficiency on the other two is extremely relevant for the work on hands. This issue is handled in the work of Ferreira et al. (2020).

Fifthly, the formulation of the unitary prices should comprise a broad and holistic view on all the factors and relations mentioned above, as proposed by the works of (Ferreira et al., 2019, 2020; Miraldo et al., 2011).

Lastly, there are exogenous factors that shape the provision of healthcare, here are highlighted those population-centered. Kuo and Lai (2013) conclude that the education level and socioeconomic status influence health status and the costs of healthcare services. Studies of Mackenbach et al. (2011) and Woolf and Braveman (2011) discuss the impact of the magnitude of inequalities generate on costs consequently in the efficiency of our HS. The conclusion underlines that fighting inequality is one of the principals of the welfare state and that the mitigation of inequality is a condition for a HS to be efficient. Hence all policies regarding healthcare should be integrated with a social perspective, or more particular for the case described efficiency should include with social inequality.

Chapter 3

Background: Clustering

Clustering is an unsupervised machine learning technique, which aggregates data instances. The resulted groups are designated as clusters. Clustering techniques label objects according to the assessment of the similarity of the observations. Thus, the groups comprise objects that are similar between them and are dissimilar when compared to data items from other clusters (Aghabozorgi et al., 2015; Karaboga and Ozturk, 2011).

Clustering can be explained as a process that has as input a set of observations unlabeled and produces as output the initial set of observations labelled and organized.

The observation, also nominated as a data instance or data object corresponds to a sole entity. Very often it is represented by a vector and its dimension is defined by the number of variables covered in the problem under study (Jain et al., 1999).

The features, attributes or variables, are the scalar components that of a data instance. Each vector component corresponds to a single feature (Jain et al., 1999).

Features can be classified into two major categories: numeric and non-numeric. The former is further divided into continuous and discrete. The non-numeric category encloses the categorical and nominal sets. To be easier to deal with the non-numeric features, these are converted into numeric values, by attributing a different value to each of the categories (Liu and Yu, 2005).

3.1 Applications and challenges

The type of problem that clustering tackles is common to many fields of knowledge, such as operational research (Brusco et al., 2012; Vakharia and Wemmerlöv, 1995), medical imaging (Nithila and Kumar, 2016), information retrieval(Charikar et al., 2004), and many others fields as biology (Jiang and Singh, 2010), psychiatry (Bzdok and Meyer-Lindenberg, 2018), and others such psychology, archaeology, geology, geography, and marketing (Jain et al., 1999). Clustering is a powerful tool used for several tasks of machine learning and data mining. Information retrieval, networks analysis, pattern recognition and classification are a few of those. It can be applied as an excellent exploratory approach to uncover hidden patterns in the data. Clustering can also be integrated into a preprocessing or postprocessing pipeline for machine learning or data mining assignment. Under these circumstances, its implementation focus on the leverage another algorithm performance concerning the data analysis (Yang et al., 2017).

Clustering is a critical tool for data analysis. One of the main reasons for this is related to the increasing data's size in recent times, as the XXI century is associated with the title of the era of big data, alongside the cloud computing. Due to the high dimensions of the average data sets, manual labelling data has become an expensive and arduous task. Thus automatic methods such as data clustering are gaining importance, reaching the top of the most well-known techniques to perform automatic labelling (Aghabozorgi et al., 2015; Alelyani et al., 2018).

3.2 Phases and components of the (clustering) process

The structure of this section was inspired in the article of Jain et al. (1999). Yet, it is complemented throughout its extension with other relevant sources of knowledge.

As already approached, the clustering can be sum up as a computational process that receives as input unlabelled data instances and that transforms it into to labelled observations. These results in the organization of the initial objects divided into clusters. This action can be decomposed into four main steps: 1) dimensionality reduction; 2) selection of the dissimilarity measure; 3) election of the clustering technique; 4) analysis and validation of the results.

Each stage influences the outcome, in such a way that for the same input, a multitude of different set clusters can be achieved. The challenge is tuning the parameters so that the output reflects the actual structure and relationship between the observations. The next paragraphs are dedicated to exploring with more detail the options and the major factors for all of the steps.

3.2.1 Dimensionality reduction

The initial phase consists of reducing the variables of the data set. This is done typically for two reasons: to minimize the noise, that inherently characterize the majority of the data, and also, to eliminate redundant features. The consequences of reducing the data's dimensions are: the algorithms have better performances and diminishing the system requirements concerning time and memory space (Alelyani et al., 2018).

Decreasing dimensions can be achieved by two approaches: feature extraction and feature selection. For the former, the number of features is reduced by executing a projection in a space with few dimensions, making the resulting features to be a (linear or non-linear) combinations of the initial batch. Feature selection is simply picking a sub-set of features from all the initially available. Hence no distorting or modification of any attributes takes places. It is chosen the variables that decrease redundancy while maximizing the relevant information for comparing and aggregating the observations.

In terms of readability and interpretability, feature selection is superior to feature extraction. Because, the extraction is transforming the initial attributes into a combination of them, while the former approach simple picks a few of them.

A couple of examples of methods are Principle Component Analysis (PCA), a way of extracting features that are the linear combinations of the original variables that better explain the data variability (Wold et al., 1987). And Information Gain, a popular information-theoretical way of assessing the discriminative profile of a variable for feature selection (Alhaj et al., 2016).

3.2.2 Similarity measure selection

The clusters are formed based on similarity. This notion can be defined as the quantification of the strength of the association between two observations. Thus, the instances that belong to the same cluster are strongly related, and both are weakly related to other data points outside their group (Irani et al., 2016). Given this, the approach for measuring the relationship between data instances has a profound impact on the results. Most of the relevant problems require the inclusion of many features, often of a multitude of types and scales. Therefore, the decision on which measure to apply can be complex, however, the performance of many clustering algorithms rely on picking the measure that best suits the input (Patidar et al., 2012). Or, in other words, choosing the measure that *a priori* best "respects" the structure and organization of the data, increasing the likelihood of the clusters that results of the process making sense.

The measure can be a metric or not. To be considered one, the measure needs to comply with the triangle inequality (Zhang, 1995). In the literature, the majority of the measures are metrics such as Minkowski and Hamming distances described in the next paragraphs (Irani et al., 2016).

Minkowski distance is a popular measure, that uses a parameter p to control the properties of the distance, expressed in Equation 3.1.

$$\text{Minkowski}(\vec{x}_i, \vec{x}_j) = (\sum_{k=1}^{d} |x_{ik} - x_{jk}|^{\frac{1}{p}})^p \tag{3.1}$$

It is a distance metric, that is also defined as a generic measure, due to the fact the using different values for p, different metrics are obtained. For example, when p $= 2$ it corresponds to the Euclidean distance, which is the standard measure for geometrical problems (all variables are numerical).

Another widely applied metric is Hamming distance. It computes the number of nominal values that differ between two feature vectors. It is typically applied for categorical variables (Pandit and Gupta, 2011).

3.2.2.A Measures for mixed data sets

When data objects comprehend both categorical and numerical variables the choice of measure should be addressed with caution. It is paramount to ensure that the calculation of distances is not distorted by the idiosyncrasies of the measures. As the most suitable metrics for numerical and categorical differ significantly (Cheung and Jia, 2013).

A straightforward approach is transforming all numerical variables into categorical, by applying a discretization method or converting all the categorical into numerical, trough dummification. Proceeded by the application of a similarity measure for purely categorical data and numerical data, respectively. Nevertheless, this approach does not capture the full information contained in the data, since subtle details are lost in the conversion processes.

Another possibility is the use one generalized criterion designed to deal with mixed data sets. This type of approach attributes different weights to features according to how uncommon are the similarities computed. For the distance calculation, only one measure is used, such as the Goodall's measure or metrics derived from it.

Lastly, it can implement a composite metric distance. This measure comprises two metrics. One that is applied solely to the categorical features and the other to the numerical variables. For example, application of Hamming distance for the categorical features and Euclidean distance for the reaming variables (Jia and Cheung, 2017).

Measuring the similarity quantifies the relationship between objects regarding the feature space. However, instances can exhibit identical behaviour along the time dimension, which is not likely to be recognized as featuring a strong connection by distances metrics (Kulkarni et al., 2015). This issue emerges in problems that involve time-series data, which corresponds to data sets that comprise information of the instances regarding several moments in time (Aghabozorgi et al., 2015).

There are a few solutions for overcoming this issue. One contemplates the use of adapted distance-measures, ie. Dynamic Time Warping, one of the most well-known methods for time-series clustering (Aghabozorgi et al., 2015). Another alternative is the application of data shape-based similarity measures (ie. Angular Metric for Shape Similarity) (Nakamura et al., 2013). The former approach handles misalignment in time, while the latter deals with misalignment regarding amplitude.

3.2.3 Clustering technique selection

Figure 3.1 depicts the most prominent clustering technique, although it should be noted that there exist appreciably more methods published in the scientific literature. Some of those can be found in the work of Saxena et al. (2017), Brusco et al. (2012) and Karaboga and Ozturk (2011).

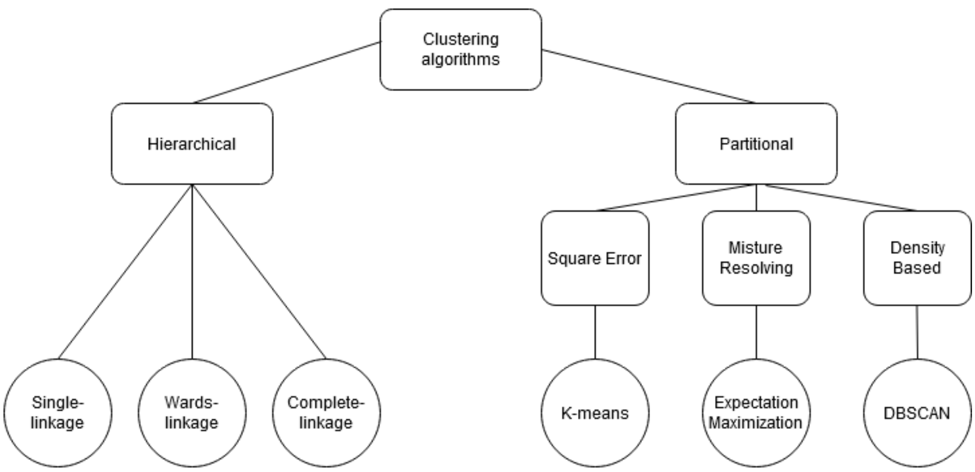

Figure 3.1: Classification of clustering techniques. Adapted from Saxena et al. (2017)

As depicted in Figure 3.1 the principal categories are hierarchical and partitional (or non-hierarchical).

3.2.3.A Hierarchical Clustering Algorithms

The methods of hierarchical clustering originate decomposition of the instances into subsets. The diagram that is generated displays a hierarchical structure. It is designated as a dendrogram. Figure 3.2 illustrates one example. In this case, the image depicts the output of hierarchical clustering with Ward's linkage criterion applied to a data set comprised of 28 public hospitals, in which the similarity metric considered was the euclidean distance.

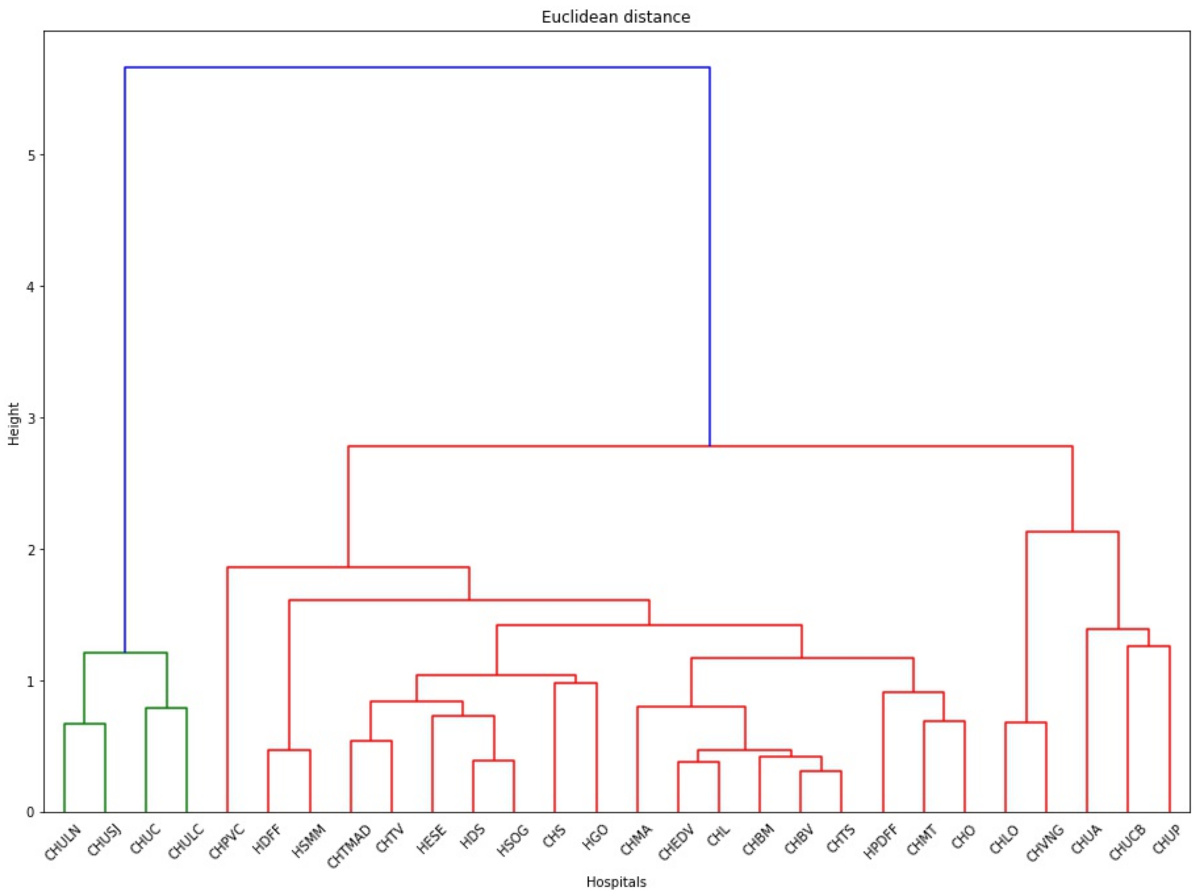

Figure 3.2: Dendrogram generated by hierarchical algorithm with Ward's linkage criterion. Distances were computed with the Euclidean metric.

The vertical axis indicates the maximum similarity distance between the instances in a cluster. On the bottom of the image height is zero, thus all the observations are separated since all are unique entities. On the contrary, at the very top, where the distance is maximum (height = 5.7), all the instances are aggregated together. This indicates that the maximum distance that objects of study are in the feature-space.

The dendrogram allows the reader to identify the homogeneous groups. Being the definition of homogeneous a parameter that is fixed by the reader, which consequently influences the number of clusters of each analysis. This parameter enables adjustments that are crucial for adequating the analysis value that best suits the purpose of each study.

Hierarchical techniques are differentiated by the linkage criterion. This parameter defines the procedure for calculating the distance between clusters. Single-linkage criterion establishes that the distance is measured between the pair of points which are closer together, but each one belonging to a different subset. Conversely, complete-linkage defines that for this computation the furthest points should be considered. Ward's linkage criterion determines that the distance is measured between the couple of objects that minimizes the total within-cluster variance. There exists a few other procedures which are not covered here (Stefos et al., 1992).

3.2.3.B Non-hierarchical clustering algorithms

The non-hierarchical algorithms yield a partition of the data, not a dendrogram. These techniques are also distinguished from the preceding category as they requires the number of subsets desired as a parameter for the model.

The partitional algorithms are classified regarding the way instances transit between subsets during the iterative process of this sort of algorithms. These techniques are also differentiated by the procedure to defined the centroid of each cluster and the method for measuring the similarity between a single instance and the clusters' centroids (Yoo et al., 2012).

Squared error methods are the most used non-hierarchical method. They exhibit good results in compact and isolated clusters. K-means is the most famous algorithm of this category.

K-means begins by setting randomly a partition, that divides the data set in k groups. It reassigns the objects according to the dissimilarity matrix, that computes the distance between the pattern and the cluster. This until a convergence criterion is achieved (ie. for more than n iterations, either the instances do not alternate clusters or the squared error does not decrease).

Density clustering algorithms aggregate objects based upon a perspective of density. This approach relies on the concept of ε-neighborhoods defined by a couple of parameters: the centre point of the region, and the value of the distance that establishes its limits. Additionally, these methods include as parameter the minimum of instances are required to belong to the neighbourhood, such that this can be classified as a cluster. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is the most utilized algorithm of this class (Saxena et al., 2017).

A mixture model is a fuzzy clustering, in other words, objects can be associated to more than one cluster, and their connection to each of the subsets has a value that describes the strength of this association. The Mixture Resolving and Mode-Seeking algorithms are applied to situations where the data items are considered to be instances of probability distributions. Thus, the aim for these techniques is not only to aggregate the data points, but also to characterize these distributions, by computing their parameters, i.e. mean and covariance. Each cluster corresponds to a generative model: a probability distribution. Typically a Gaussian or a multinomial (Stefos et al., 1992).

Each technique uses a unique approach, thus the pros and cons of using algorithms also differ among them. The hierarchical algorithms have an important advantage that is the visualization capacity, through the dendrogram, which allows to understand (with some confidence) the number of clusters and see how similar are objects belonging to the same cluster. On the other hand, hierarchical techniques required more computational power and time, than non-hierarchical ones, therefore it is a drawback to be considered especially with large data sets. Another advantage of partitional algorithms is their higher accuracy. Although, their results have a considerable variation due to the random selection of the centroids of the initial clusters.

3.2.4 Analysis and validation of the results

This section comprises two important tasks: validation and analysis of the results. On one hand, the validation process evaluates the meaningfulness of the clusters obtained. On the other, the analysis aims to interpret the same results, considering the context of the problem and the significance of all the variables.

In 1988, Jain and Dubes define cluster validation as the "*procedures that evaluate the results of cluster analysis in a quantitative and objective fashion*" (Jain and Dubes, 1988). Indexes are implemented because when applied provide output values (quantitative) and the (correct) application of the same metrics by different persons guarantees equal results (objective). A solid assessment of the validity of clusters should comprise three aspects: the comparison of clustering algorithms, avoidance of identification of patterns in noise and the determination of the number of clusters.

There exist three main approaches: internal, external and relative. The former considers only intrinsic characteristics of the clusters in the assessment. The external evaluates the fitness of the subsets by comparison with external information concerning the structure of the data. While the latter approach evaluates the results regarding the consistency of those outcomes with different clustering methods (Rendón et al., 2011).

As stated in Section 3.1, clustering is an excellent tool for exploring data and unveiling relations and patterns between instances. However, the most adequate clustering technique depends on the nature of data that is being analysed. To identify the best method for each case, internal and external criteria are used (Larsen and Aone, 1999).

3.2.4.A Validation: External indexes

External indexes require prior knowledge of the structure of the data. This insight is relative to the organization of the data and thus it is referring to the ability of methodology under evaluation grouping the instances correctly. The correct labelling of the data objects is termed as *ground truth*. The next paragraphs describe a couple of external criteria: F-measure and adjusted Rand index (Rendón et al., 2011).

The F-measure index relies on concepts of information retrieval such as recall and precision. Recall measures for each class the capacity of the algorithm to label rightly all the expected observations. Precision, measures for each cluster obtained by the algorithm, the level of correctness of the labels applied. These two concepts are computed as showed in following equations:

$$Recall(i,j) = \frac{n_{ij}}{n_i} \tag{3.2}$$

$$Precision(i,j) = \frac{n_{ij}}{n_j} \tag{3.3}$$

For both Equation 3.2 and Equation 3.3, the *i* and *j* correspond to the class and to the cluster/label attributed, respectively. n_{ij} represents the number of objects of belonging to the class *i* that are in the cluster *j*.

The index F-measure is calculated using the formula expressed in Equation 3.4.

$$F(i,j) = \frac{2 \times Recall(i,j) \times Precision(i,j)}{Precision(i,j) + Recall(i,j)} \tag{3.4}$$

This index has a range of [0,1] and the higher the better is the clustering quality.

Another criterion available is the adjusted Rand criterion. The computation of the criterion involves the analysis of the contingency table that depicts the correspondence between the classification of the samples in both partitions, obtained from the same data set. Given partitions U and V, the contingency table is built, Table 3.1. n is the number of instances, R is the cardinality of the groups that are formed in the former partition, and C the number of subsets for the latter partition. This validation index is valid for in cases where C $\neq$ R.

Table 3.1: Contingency table for comparing partitions U and V. Source Santos and Embrechts (2009)

Partition		V				
	Group	v_1	v_2	$\cdots$	v_C	Total
U	u_1	t_{11}	t_{12}	$\cdots$	t_{1C}	$t_{1.}$
	u_2	t_{21}	t_{22}	$\cdots$	t_{2C}	$t_{2.}$
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	u_R	t_{R1}	t_{R2}	$\cdots$	t_{RC}	$t_{R.}$
Total		$t_{.1}$	$t_{.2}$	$\cdots$	$t_{.C}$	$t_{..} = n$

Note that in Table 3.1, the number of instances clustered in the group *cth* of partition V and included in the r^{th} subset of partition U is indicate in the entry t_{rc}. Using the same notation the index is computed according to Equation 3.5

$$\text{Adjusted Rand Index} = \frac{\binom{n}{2}\sum_{r=1}^{R}\sum_{c=1}^{C}\binom{t_{rc}}{2} - [\sum_{r=1}^{R}\binom{t_{r.}}{2}\sum_{c=1}^{C}\binom{t_{.c}}{2}]}{\frac{1}{2}\binom{n}{2}[\sum_{r=1}^{R}\binom{t_{r.}}{2} + \sum_{c=1}^{C}\binom{t_{.c}}{2}] - [\sum_{r=1}^{R}\binom{t_{r.}}{2}\sum_{c=1}^{C}\binom{t_{.c}}{2}]} \tag{3.5}$$

This index is labelled as one of the most successful external indexes for validating clustering results. The range and interpretation of the result of the application of the criterion coincide with the preceding one. It ranges between zero and one, and the closer to the unity higher is the validation of the clustering (Santos and Embrechts, 2009).

3.2.4.B Validation: Internal indexes

These set of criteria emit the judgment concerning the quality of the results based upon the sole information of the data. There is not a *groundtruth*, unlike for the external indexes. In general, this type of criterion combines two concepts: compactness and separability. Compactness refers to how close are the data items in each cluster, which is measure by the sum of squared error within clusters, termed as *WSS*, equation 3.6. And separability, which is an indicator of the distance between clusters. This is measure by the sum of squared errors between clusters, commonly refereed as *BSS*, see equation 3.7 (Lee et al., 2012).

$$\text{WSS} = \sum_{k=1}^{K} \sum_{x_i \in C_k} d(x_i, c_k)^2 \tag{3.6}$$

$$\text{BSS} = \sum_{k} |C_k| d(c_k, \vec{x})^2 \tag{3.7}$$

Clustering is designed to output the groups in which the highest level of compactness and separation possible. Silhouette presents itself as a criterion that can assess the results covering both these two critical aspects. This metric assesses the quality of the clusters obtained considering the difference between the compactness and separability, it was proposed for the first time in the work of Rousseeuw (1987). The computation of this index is represented in equation 3.8.

$$Silhouette = \frac{1}{N} \sum_{i=1}^{N} \frac{BSS(k) - WSS(k)}{\max WSS(k), BSS(k)} \tag{3.8}$$

The higher the value of the silhouette coefficient the higher is the quality of the clustering.

3.3 State of art on clustering hospitals

This present section summarises the state of the art concerning the clustering of hospitals. The employment of this machine learning tool to generate subsets of healthcare providers is driven by multiple motives: optimization of delivery of care, planning the construction of new units, categorization, funding purposes and benchmarking. Despite the broad range of reasons for executing this analysis the scientific literature covering this topic is scarce. Albeit this fact, hereby are outlined the most relevant information of the most recognized articles in the theme, eight in total.

Preprocessing pipeline, similarity measure and evaluation of the results on their validation are relevant aspects in the process. Thus, the appreciation of the articles included these dimensions.

Firstly, the study of Hariyanti et al. (2019) involves the application of K-means and hierarchical algorithms (with single and complete linkage criteria) to Indonesian hospitals with the purpose of classifying these healthcare units according to the established law.

Secondly, Belfin et al. (2018) details the experience to identify the areas where the scarcity of healthcare service is most pressing in India. The study is conducted to support the decision for defining the location of a novel healthcare units in India. Hierarchical clustering with complete linkage criterion is the metric used.

Thirdly, hierarchical clustering with Ward's method was the technique applied to data regarding three hospitals of Singapore with the aim of aggregating hospital medical specialities based on their utilization by patients. This experience is reported in You et al. (2014).

Fourthly, the most prevailing reason for performing clustering hospitals is to improve benchmarking results. Data Envelopment Analysis (DEA) is a powerful methodology to generate information on benchmarking. This approach is a non-parametric technique that evaluates and identifies the most efficient entities regarding different dimensions adjusted to each case. Despite the remarkable success of this tool, there exist constrictions which limit the application and outcomes of the method. A couple of the most significant are: the declining in performance with the increment of variables, and sensitivity of results regarding the input and output features covered in the analysis (Cantor and Poh, 2018). There are many approaches possible to overcome these drawbacks. Here are highlighted the approaches of machine learning techniques of unsupervised learning (clustering) (Flokou et al., 2011; Wei et al., 2012), the optimizations of the weights in the DEA process (Cinaroglu, 2019), and the aggregation of the healthcare units into homogeneous groups considering the environmental factors and volume of outpatients Najadat et al. (2020).

Fifthly, the aforementioned reported experiences involve the application of a narrow range of techniques, predominated by hierarchical and K-means methods. However, the publication of Byrne et al. (2009) it is very interesting in this context since it proposes a novel approach for grouping hospital units. The proposed method is based upon Nearest-Neighbour (NN) algorithm, offering advantages over the more traditional methods: 1) the centre of clusters is always a hospital (not a centroid/average point); 2) higher cohesion of subsets; 3) more appealing results favouring the applicability of in supporting decision-makers and researchers.

Taking into account all the supra-mentioned articles is possible to conclude that for clustering hospitals the most applied methods are hierarchical clustering (5 out of 8 papers) and the K-means (4 out of 8 studies). Additionally, K-NN clustering method and multiple correlation model were implemented each of them once for clustering this type of health care units.

Chapter 4

Case Study

This dissertation proposes to achieve three major goals, as outlined in Section 1.2. First to define the parameters of the clustering model that replicates the current hospital classes. Second, to generate hospital groups following the same procedure of the previous step, considering solely the features used in the original analysis for both the most recent data and the data contemporary to the first presentation of the model. The third consists of repeating the process but, incorporating the dimensions of access, quality and environment as well. An experimental framework that comprises threes phases was designed to meet these objectives.

This chapter contains several sections. The first section (Section 4.1) indicates the healthcare units under the scope. Section 4.2 establishes the temporal periods covered in the analysis. Section 4.3 lists all the set of features accounted in this work. Moreover, the choice of the variables is contextualized and the corresponding sources of information are indicated. Section 4.4 details the proposed methodology to achieve all the objectives of the study. At last, Section 4.5 outlines the methodological approaches to overcoming the unconformities of the data.

4.1 Target hospitals

This project focus on Portuguese general public hospitals that currently have a juridical status of EPE. Thus, being excluded from the study both specialized hospitals and general hospitals with different juridical and administration frames, such as SPA and LHU. These exclusions are applied due to disparity concerning the clinical activity and divergence regarding the governance of the units dictated by the legal-administrative framework. Furthermore H Braga EPE is not considered as for the period analysed in this study it was a hospital PPP. Figure 4.1 depicts the currently establishes classes for the 28 hospitals covered in this work.

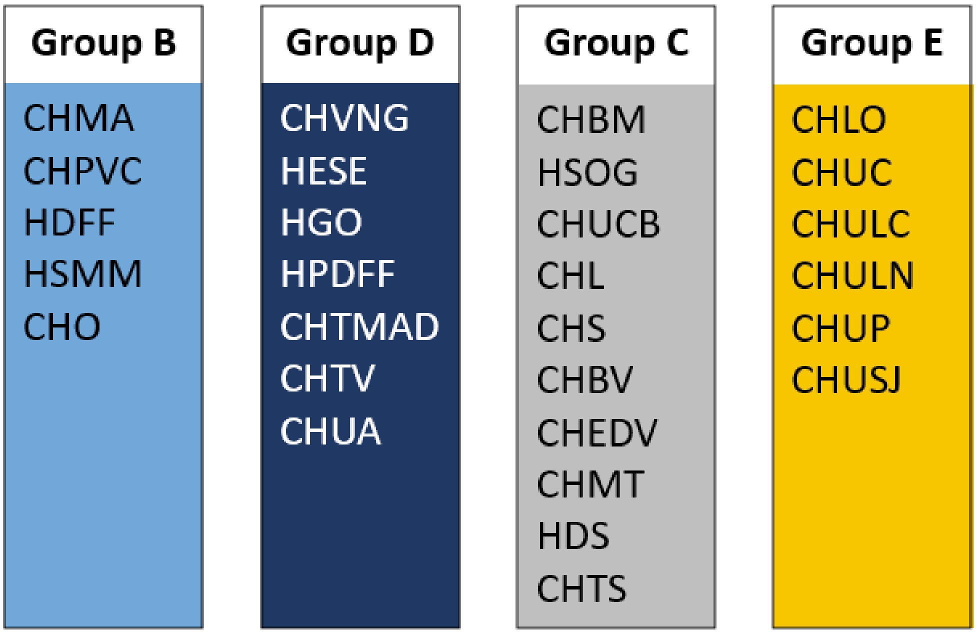

Figure 4.1: Current established groups for general public hospitals EPE

4.2 Selected periods for analysis

The main structure of the study is set upon the two moments, which are hereinafter referred to as scenarios. The first scenario regards the data considered in the original clustering process that lead to the present hospitals categories, which have been implemented since 2013 in the funding schemes. The guidelines for the production and financial agreement of that year were published on the November 2012 (ACSS, 2012). Although, the creation of the hospital groups was presented before in a conference of October 2011 (Candoso et al., 2011). The information available leads to some uncertainty concerning the sources of the data. Thus a supposition was made that all the data used was the most recently available at the time contemporary to the creation of the clusters, so 2010 was the year that matches these expectations. This scenario was labelled as CTC, with the initials from the expression contemporary to [the] creation. The other time frame used was the present scenario. Like the name suggests it corresponds to the actual time-frame. However, due to the delay that exists between the publication of reports and data regarding a certain period, the majority of the data in this time-frame corresponds to 2019. The present scenario utilizes information regarding the year 2019. This decision is supported by two reasons. First, the pandemic of COVID-19 disrupted our modern societies with a profound impact on the activity of healthcare providers. Therefore the data available regarding the few months of 2020 did not satisfy well the scope of the study. Second, the results on the indicators are considered yearly, so that seasonal fluctuations that encompass the summer holidays and flu season do not distort the analysis.

4.3 Hospital and contextual variables

The presentation of variables is done below according to its domain. Section 4.3.1 details the features contemplated in the original process. Section 4.3.2 lists the features that serve as indicators for assessing the level of access to the hospital services by the population. Section 4.3.3 describes the features that evaluate the quality of the delivery of care. Finally, Section 4.3.4 identifies the variables that characterise the context in which the provision of care is performed.

4.3.1 Original features: production and capacity variables

The set of features utilized in the original process of clustering is discriminated in the work of Nunes (2020). These are listed in Section 2.3. The first phase of the work aims to replicate this process. However, the existence of restrains conditioned the pursue of this goal, since it was precluded the access to some information included in the original protocol. Seven proxy variables were used to overcome this matter, as depicted in Table 4.1. Table 4.2 lists the original variables which could not be accessed and the respective replacing features used.

The experience is designed to consider the actual hospital network of the NHS and to implement the same criteria in all the scenarios covered. This principal is respected with the exception of the hospital categorization variable. The initial intention was to consider the hospital classification from which the actual referral network was built upon, established in *Carta Hospital* published in 2014.[1] Although, it is not reasonable to use this criterion in CTC scenario as at the time this classification did not exist yet. Therefore, it was chosen to use instead the classification of the public hospitals contemporary at that moment that was the classification of the permanent care service of healthcare units, defined in the dispatch no. 5414/2008 [2]. This information coincides with the already incorporated feature urgency typology. Consequently, the information captured in both scenarios is the same, but the number of features differs: the CTC scenario is tested with 18 variables while the Present scenario uses 19. As the urgency typology is only used one time, and it encompasses the information of the categorization of the hospitals in the CTC scenario too.

There are a couple of notes to be made regarding the calculation and assumptions made regarding the features aforementioned for the CTC scenario. First, the computation of the variable of emergency episodes was the result of the sum of all the type of urgency episodes. It includes the paediatrics, psychiatric, obstetrics and general urgency episodes. Second, the feature of equivalent patients was computed as the weighted sum of the hospitalization events, medical appointments, urgency episodes and the day hospital care production. The weights were the CMI of the medical and surgical treatments, according to the service provided in each case.

[1] Decree no. 82/2014 `https://data.dre.pt/eli/port/82/2014/04/10/p/dre/pt/html` accessed on 08/03/2020

[2] Dispatch no. 5414/2008 `https://dre.pt/web/guest/pesquisa/-/search/3378909/details/normal?q=5414%2F2008` accessed on 08/03/2020

Table 4.1: List of features considered in this analysis to reproduce the original clustering process for both scenarios

Variable	ACSS protocol	Type	Scenario: CTC Source - publication year	CTC Year	Present Source	Present Year
Urgency typology	Original feature	Categorical	Decree n. 5414/2008 [f]- 2008	2008	Contract programs - 2019	2019
University hospital		Categorical	Contract programs - 2013	2013	Contract programs - 2019	2019
Medical hours		Numerical	TP - providers of medical services	2011	TP - providers of medical services	2018
Beds			Report of MH - 2013 [a]	2012	ACSS Benchmarking - Utilized capacity	2017
Urgency episodes			Report of MH - 2013 [a]	2012	TP - activity of emergency service	2019
Hospitalization episodes			Report of MH - 2013 [a]	2012	TP - Hospitalization activity	2019
Medical appointments			Report of MH - 2013 [a]	2012	TP - hospital medical appointments	2019
Equivalent patients			Report of MH - 2013 [a]	2012	Annual estimation	2019
CDTT Total			Report of MH - 2013 [a]	2012	Management Reports [i]	2018
Ratio of resident physicians			TP - employees per professional group	2011	TP - employees per professional group	2019
Operation rooms			Report of MH - 2015 [b]	2014	Report of MH - 2015 [b]	2014
Beds in specialized units			Report of MH - 2015 [c]	2012	Report of MH - 2015 [c]	2012
Hospital categorization	Proxy	Categorical	Decree n. 5414/2008 [f]- 2008	-	Decree n.82/2014 - 2014	2014
Internal CDTT		Numerical	Report of MH - 2013 [a]	2012	Management Reports[i]	2019
CMI medical ambulatory			Contract programs - 2013	2011 [g]	Contract programs - 2019	2015 [g]
CMI surgical ambulatory			Contract programs - 2013	2011 [g]	Contract programs - 2019	2015 [g]
CMI medical hospitalization[h]			Contract programs - 2013	2011 [g]	Contract programs - 2019	2015 [g]
CMI surgical hospitalization[h]			Contract programs - 2013	2011 [g]	Contract programs - 2019	2015 [g]
Nurses			DGS report - 2015 [d]	2012	TP - employees per professional group	2020

TP - Transparency Portal.
[a] Report of the work group for assessing the national situation of medical heavy equipment for the MH.
[b] Report of the Work Group for assessing the national situation of the operation rooms for the MH.
[c] Report of the Work Group for assessing the national situation of the Intensive Care Units (ICU)s for the MH.
[d] Report on resources and production activity of the healthcare providers of the NHS in 2012.
[e] also used as a proxy. See Table 4.2 for further details.
[f] Classification based on the urgency services provided by each unit. It is same variable of 'Urgency Typology'. To deal with this, the scenario CTC will be only consider the Urgency Typology once - to avoid redundancies.
[g] the source of this information are the contract programs of the year 2013, although the CMI values in these documents are actually reporting to the year of 2011.
[h] in the present scenario the CMI medical hospitalization and the CMI surgical hospitalization are merged into just one metric the CMI hospitalization.
[i] In certain cases this information was found in the institutional website of the hospital. The publication of this data is framed in the dispatch no. 10430/2011.
[*] This was the only available source of information found with complete data with respect to all the units analysed. It was considered as an immutable feature, for the time frame studied.

Table 4.2: List of proxies variables identified in Table 4.1, and the correspondent original features which they are replacing.

Variable used in the study	Proxy to the variable used in the ACSS protocol: Variable i	Variable ii	Variable iii
Hospital Categorization[1]	Range of medical appointments for differentiated care	-	-
Internal CDTT[2]	Equipment	Differential equipment	-
CMI medical ambulatory **CMI medical hospitalization**[3] **CMI surgical ambulatory** **CMI surgical hospitalization**[3]	Range of DRG	Range of complex DRG	Ratio of complex DRG
Nurses	Nursing hours	-	-
Medical appointments	External consultation cabinets	Ratio of medical appointments for differentiated care	-

[1] Decree no.82/2014
[2] CDTT stands for complementary and diagnostic tests and therapies
[3] in the present scenario the CMI medical hospitalization and the CMI surgical hospitalization are merged into just one metric the CMI hospitalization;

4.3.2 Access features

The indicators used for evaluating the access to the healthcare services were the pair of metrics available in the ACSS Benchmarking platform, illustrated in Table 4.3.

As depicted in Table 4.3 the information reported by the variables considered in the CTC scenario respects to 2012 year. This the earliest year from which the information concerning the access domain is available.

Table 4.3: Metrics considered for assessing the access of the population to hospital healthcare services.

Variable	Scenario			
	CTC		Present	
	Source	Year	Source	Year
Medical appointments performed under the appropriate time **Surgeries performed withing the guaranteed maximum response time**	Benchmarking*	2012	Benchmarking*	2014

* https://benchmarking-acss.min-saude.pt/BH_AcessoDashboard accessed on 22/08/2020;

4.3.3 Quality features

Hereby are described the metrics chosen for assessing the quality of the services provided by the healthcare units, which correspond to all the indicators accessible on this issue in the benchmarking platform. This situation is shown in Table 4.4.

The situation expressed in the precedent section (Section 4.3.2) concerning the time-frame that access features report is very similar to the case of quality variables. Notwithstanding there is a difference to be stated. The ACSS platform only contemplates information regarding the quality of the services since 2014, thus for the CTC scenario the data used correspond to this year, see Table 4.4.

Table 4.4: Variables used for assessing the quality of the health services provided by the public hospitals included in the study.

Variable	Scenario			
	CTC		Present	
	Source	Year	Source	Year
Pressure ulcer rate **Blood stream infectious rate related central venous catheter** **Pulmonary embolism & deep vein thrombosis rate on the post-surgery** **Sepsis on the post-surgery** **Ratio of instrumented vaginal births with 3^{rd} and 4^{th} degree lacerations** **Ratio of non-instrumented vaginal births with 3^{rd} and 4^{th} degree lacerations**	Benchmarking*	2014	Benchmarking*	2019

* https://benchmarking-acss.min-saude.pt/BH_SegurancaDashboard accessed on 21/08/2020;

4.3.4 Environmental features

The research work conducted for this dissertation found no database either document that contained aggregated information on education, socio-economic and demographic factors regarding the population covered by each hospital. Neither the original grouping process of hospitals, neither the platform of benchmarking of ACSS contemplates the environmental variables served by the healthcare units. Hence, the information collected for this type of data it is not originated from the usual source, referred in the last sections. It was extracted from INE, as depicted in Table 4.5. Therefore a strategy was drawn and implemented to build a data set with this information.

All the national statistical data on the dimensions mentioned above are organized and made available in the NUTs frames. NUTS are the french initials for Nomenclature of Territorial Units for Statistics, used by the European Statistical Office (Eurostat), to divide hierarchically the territories. The updated list of NUTS can be found in the European Commission Regulation No 1319/2013.[3]

NUTs contemplate three hierarchical levels: I - continent and islands, II - regions, III - districts. The latter framework corresponds to municipalities. This is the level that bests suits the purpose of the work since it is the most detailed level available.

The association of hospitals and the environmental data had to be forged. To achieve it is necessary a link that connects hospitals and NUTs III. This is established with the Referral Network (RN) for the speciality of Neurology. [4]. This particular medical speciality is chosen for two major reasons. First, all the hospitals under analysis offer this speciality according to the legislation in force. [5] Second, this particular RN clearly shows the flux of transferring patients between the different units, for the level of care and their residence area (the majority is determined by municipalities, but there are cases where it is determined by the parish council).

According to the Neurology RN, a patient can be referred up to three hospitals. These levels are addressed as the direct, secondary and tertiary indirect areas of influence for each hospital. This fact originates different circumstances for the association between a population of a geographic unit and hospitals. For instances, there are populations such as the one of Maia, which for all the hospital levels of care is referred to CHUSJ. While, on the opposite situation, there is the population of Montijo, which for the first response is referred to the CHBM, then if more differentiate care is required the patients are then transferred to the HGO, and for the most differentiate healthcare services will need to be moved to the CHULC. Thus, to deal with this diversity the approach followed weighted differently the populations according to the position of the hospital in their referral system (1st, 2nd (indirect) or 3rd (indirect). The weights attributed are depicted in Table 4.6.

With this information, it was constructed a data set that associates 279 geographical units composed by 264 municipalities and 15 different aggregates of parish councils.

The RH of Neurology does not include hospitals CHPVC and HSMM. This restricts the possibility of associating environmental information with these two units. To overcome this challenge, information on the webpage of the MH regarding these two specific hospitals on their direct influence areas was used. [6] [7]

Many indicators and metrics that describe aspects of the three topics that are incorporated in this project: education, demography and socio-economic factors. The following paragraphs are dedicated to explicit the reasoning behind the choices of the features used.

The size of a population served by a hospital is an important value to be taken into account in the planning of a hospital. Another fundamental demographic element for the activity and costs of healthcare

[3] `http://data.europa.eu/eli/reg/2013/1319/oj` accessed on 08/09/2020
[4] `http://www.acss.min-saude.pt/wp-content/uploads/2016/10/RR_Neurologia.pdf` accessed on 20/08/2020
[5] Decree no. 82/2014 `https://dre.pt/pesquisa/-/search/25343991/details/maximized` accessed on 22/09/2020
[6] `https://www.sns.gov.pt/entidades-de-saude/hospital-santa-maria-maior-epe-barcelos/` accessed on 22/09/2020
[7] `https://www.sns.gov.pt/entidades-de-saude/centro-hospitalar-povoa-de-varzimvila-do-conde-epe/` accessed on 22/09/2020

Table 4.5: Variables used for assessing the environmental reality of the population served by each hospital.

Variable	Scenario			
	CTC		Present	
	Source	Year	Source	Year
Resident population	Censos [a]	2011	Annual estimation [f]	2019
Level of education	Censos [b]	2011	Annual report[g]	2019
Average income	Annual report [c]	2011	Annual report[c]	2018
Purchase power	Annual report [d]	2011	Annual report[d]	2017
Proportional of elders in the population	Censos [a]	2011	Annual estimation [f]	2019
Longevity index	Annual report [e]	2011	Annual report [e]	2019

[a] https://www.pordata.pt/Municipios/Popula%c3%a7%c3%a3o+residente+segundo+os+Censos+total+e+por+grupo+et%c3%a1rio-19 accessed on 20/08/20020;
[b] https://www.pordata.pt/Municipios/Popula%c3%a7%c3%a3o+residente+com+15+e+mais+anos+segundo+os+Censos+total+e+por+n%c3%advel+de+escolaridade+completo+mais+elevado-69 accessed on 20/08/2020;
[c] https://www.pordata.pt/Municipios/Ganho+m7%c37%a9dio+mensal+dos+trabalhadores+por+conta+de+outrem+total+e+por+n7%c37%advel+de+qualifica7%c37%a77%c37%a3o-279 accessed on 20/08/2020;
[d] https://www.pordata.pt/Municipios/Poder+de+compra+per+capita-118 accessed on 20/08/2020;
[e] https://www.pordata.pt/Municipios/%c3%8dndice+de+longevidade-457 accessed on 20/08/2020;
[f] https://www.pordata.pt/Municipios/Popula%c3%a7%c3%a3o+residente++estimativas+a+31+de+Dezembro+total+e+por+grupo+et%c3%a1rio-137 accessed on 20/08/2020;
[g] https://www.pordata.pt/Municipios/Popula%c3%a7%c3%a3o+residente+com+15+e+mais+anos+total+e+por+n%c3%advel+de+escolaridade+completo+mais+elevado-802 accessed on 20/08/2020 ;

providers is the age of the patients. The impact of this variable in the costs of the services delivered is illustrated by Figure 4.2. The U-shaped graphic age/costs for HS is under the basis of the literature that urges the need of the systems to adapt to the increasing pressure of ageing of the populations, in which Portugal is represented (Oliver et al., 2014; Rynning, 2008). To cover this matter it is considered the proportion of elders in the population and the longevity index. The latter component is the indicator that expresses how ageing are the elders of a region because it is computed as the ratio between people with more or equal 75 years old over the people with more or equal 65.

As stated in Section 2.5, education and socio-economic conditions are key factors in both the health status and the activity of the healthcare units that served a certain population, and naturally, these elements are interconnected and influence mutually. To incorporate these elements the level of education and medium-income were considered. Additionally, inequality is a very relevant factor to be in the consideration due to its reported influence on the HS, also mentioned in Section 2.5. Therefore, purchase power is included in the analysis, which can reveal the dissimilarity among income of a population that is partially hidden the computation of the averaging process.

4.4 Proposed methodology

As stated at the beginning of the chapter the experimental work comprises three phases. The first component is addressed in the next section. Section 4.4.2 details the second and third phases of the experimental framework. Section 4.4.3 describes briefly the process of acquisition and integration of the data utilized in the study. Section 4.4.4 outlines the preprocessing pipeline implemented at the beginning

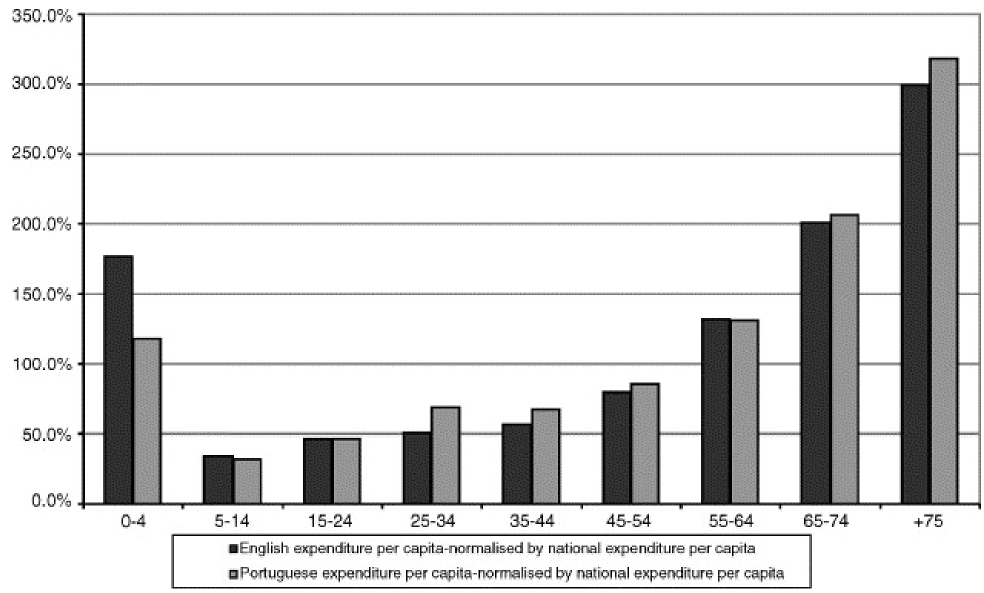

Figure 4.2: Portuguese and English healthcare costs according to age. The values were normalised by the corresponding national expenditure per capita. Source: Oliveira and Bevan (2003)

Table 4.6: Weights attributed in the clustering model to the environmental variables concerning the NR for Neurology for each population

Variable	Weights D [1]	Weights Ind 2 [2]	Weights [3]
Population with 1 unit in the RN	1	-	-
Population with 2 units of the RN	0.8	0.2	-
Population with 3 units of the RN	0.7	0.2	0.1

[1] Abbreviation for weights of the direct area of influence of the hospital;
[2] Abbreviation for weights of the secondary (indirect) region of influence;
[3] Abbreviation for weights of the tertiary (indirect) area of influence of the hospital;

of all the three phases.

4.4.1 Phase 1: Clustering hyperparameterization for the replication of hospital grouping model

The first phase entails the identification of the clustering procedure that generates the closest results concerning the actual hospital grouping. This comprises the identification of the similarity metric, clustering algorithm and the number of clusters that applied to the available data leads to this outcome. The designed framework was inspired by the methodology used in the process that is an attempt to be replicated, which is depicted in Figure 4.3.

Figure 4.4 illustrates the scheme of phase 1. First, the data set (original variables in the CTC scenario) is submitted to the preprocessing process, which is addressed in Section 4.4.4. Then, a range of clustering methods presented in Section 4.4.1.A is applied to the mentioned data set. The produced results are subsequently analysed and validated. The latter couple steps are addressed in Section 4.4.1.B.

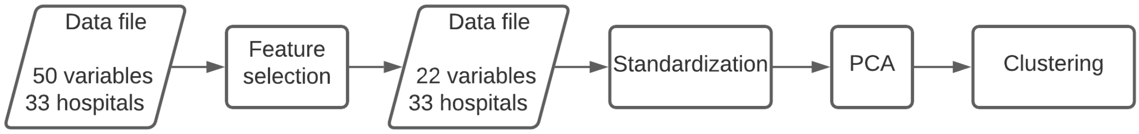

Figure 4.3: Methodology of the original process of clustering hospitals that led to the present groups. Source: ACSS (2012)

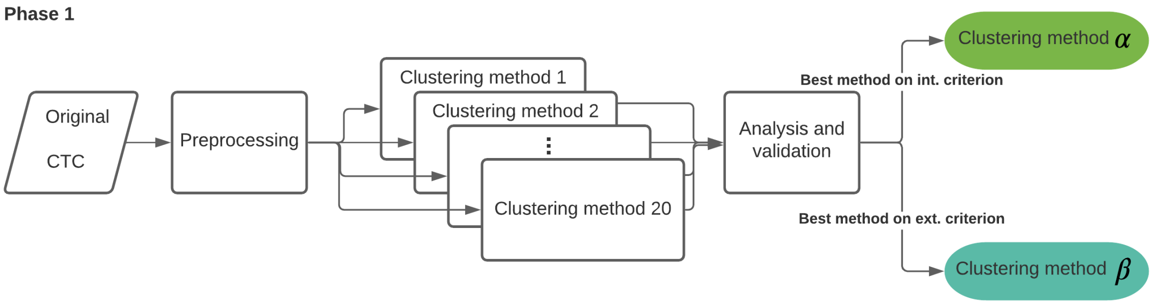

Figure 4.4: Scheme of the phase 1 of the proposed methodology. int. - internal; ext. - external

4.4.1.A Clustering methods tested

For this task, several combinations were used. The choice of algorithms to be tested was based on the information available by the ACSS, regarding the procedure applied, and also on the state of art for clustering hospitals. Table 4.7 illustrates the different combination of approaches used.

Experiences were made with three major types of algorithms: K-means, hierarchical clustering and DBSCAN. The hierarchical clustering algorithms were used with three different linkage criteria: Ward's, single and complete linkage. For all of these different approaches, four distances metrics were used, forming the 20 combinations that are expressed in table 4.7.

K-means (with Euclidean distance) was chosen due to the large consensus concerning the application of this method for grouping clustering in the state of the art, see Section 3.3. K-means with non-euclidean was implemented to overcome the main shortcomings of the traditional K-means that was conceived to deal only with numerical features. Hierarchical clustering is the other clustering approach which gathers the consensus in the literature for this type of tasks. As covered in the Section 3.3, there was an innovative application of K-NN clustering to hospital grouping reported in Byrne et al. (2009). Even though it is an interesting approach, there is another method which shares the advantages of K-NN method and that follows a similar procedure on aggregating elements, by classifying the data points into a core, border points according to their distance and the predefined number of other points present. This method is DBSCAN, described in Section 3.2.3.B. Furthermore, it identifies outliers among samples. This latter aspect, contrasts with all the other algorithms used, that do not possess this ability.

Multiple correlation algorithm is a clustering technique designed for dealing with data sets with high dimensionality (Kriegel et al., 2009). That is not the case of the data studied in this work, therefore this

Table 4.7: List of all the different clustering methods used for grouping the sample. Each combination is composed of a clustering algorithm, a similarity metric, and for hierarchical clustering methods it is also defined a linkage criterion

ID	Algorithm	Metric	Linkage Criteria
1	K-means	Man.	-
2		Euc.	
3		Euc. + Ham.	
4		Man. + Ham.	
5	Hierarchical	Man.	Complete
6		Euc.	
7		Euc. + Ham.	
8		Man. + Ham.	
9		Man.	Ward's
10		Euc.	
11		Euc. + Ham.	
12		Man. + Ham.	
13		Man.	Single
14		Euc.	
15		Euc. + Ham.	
16		Man. + Ham.	
17	DBSCAN	Man.	-
18		Euc.	
19		Euc. + Ham.	
20		Man. + Ham.	

ID - [Methodology] Identification number; Man. - Manhattan; Euc. - Euclidean; Euc. + Ham. - Euclidean for numerical features and Hamming for categorical; Man. + Ham. - Manhattan for numerical features and Hamming for categorical

method is not included.

4.4.1.B Analysis and validation of results

The analysis and validation of the subsets that result from the clustering process comprise five perspectives: external validation, internal criterion, evaluation of the statistical significance, best numerical predictor and most informing categorical variable.

First, the external criterion applied in this work is the adjusted Rand index. This index evaluates the agreement between the experimental results of the clustering methods against the established groups (*ground truth*), illustrated in Figure 4.1. Considering that the primary goal of this phase concerns the replication of the original model, this metric plays a critical role in identifying the method that fully mimics the process, or the one that gives the closest output. The adjusted Rand index was chosen, since this is one of the most recognised tools for assessing the clustering analysis, having the capacity to adequately evaluate clusters with a different number of subsets (Santos and Embrechts, 2009).

Second, the internal criterion implemented was the silhouette. This metric assesses the capacity of each method to group the healthcare units, thus allowing the identification of the method the best groups the providers. The silhouette is a robust metric which encompasses the two fundamental dimensions of aggregation of data instances: cohesion and separability (Thinsungnoena et al., 2015).

Third, the statistical significance, p-values, of the groups of hospitals that each different tested methods outputs were calculated. This assessment was conducted by applying data randomization techniques to the original data set. This randomized consisted of permuting the values in every column, obtaining each time a new dataset. Which was after used as input for the clustering algorithms. The algorithm outputs a group of clusters, from which its' silhouette is computed. The p-value is given by the probability of the silhouette of the original data set being inferior to the randomized data sets.

Fourth, analysis of variance (ANOVA) is the statistical approach used for identifying the two most relevant numerical features regarding the predicting of the grouping of hospitals. The interpretability is a key factor of these results. Thus, for achieving this, the data set used will not be applied the PCA, as it will erase the interpretability aspect. Therefore, the results will not be an exact match of the protocol followed (PCA was applied), but it will be very similar and it is the best compromise technically possible.

Resorting to this method was done assuming that the distribution of the hospitals is normal, all the samples have equal variance and the hospitals are independent of each other (Armstrong et al., 2000). To ensure that the first two criteria of the statistical test were met the data set was previously submitted to a normalization. The latter assumption was respected as hospitals are independent units for what the analysis concerns.

The assessment of the best numerical predictors for the DBSCAN results was also handled slightly differently than the other clustering methods. For the reasons explained in the previous section, the same procedure was applied here. Consequently for this algorithm only contemplated the hospitals that were not catalogued by the algorithm as outliers.

Fifth, to apply the previous task to the categorical variables Chi-squared statistical test was used. The precedent paragraph applies here too by replacing only the word of numerical to categorical [predictors].

4.4.2 Phase 2 & 3: Impact of time and access, quality and environmental features in hospital groups

Phase 2 and 3 comprise the application of the methodology that provides the results that best aggregate the healthcare units and the one that best replicates the original results. Phase 2 focus on the study of the grouping of hospitals concerning the original features and its evolution along the time dimension. It computes the clusters that result from the application of the two methods identified in Phase 1. α correspond to the method that best aggregates the providers, and β the method that best replicates the established groups. The selection of the mentioned techniques regards the data set that describes the units in the CTC scenario with the original variables.

Figure 4.5 depicts the framework for phase 2 and phase 3 of the work. The clustering method α and β are the techniques that are picked from the set of tested approaches in Phase 1, as depicted in Figure 4.4.

These phases involve the construction of decision trees to characterize of the subsets to promote a more complete interpretation and analysis of the clusters. This associative model is addressed in Section 4.4.2.A. Furthermore, for both the scenarios it is evaluated the financial impact that the integration of the proposed novel division of the hospitals in the funding scheme would generate. This process is detailed in Section 4.4.2.B. Additionally, for both the scenarios the financial impact and the characterization

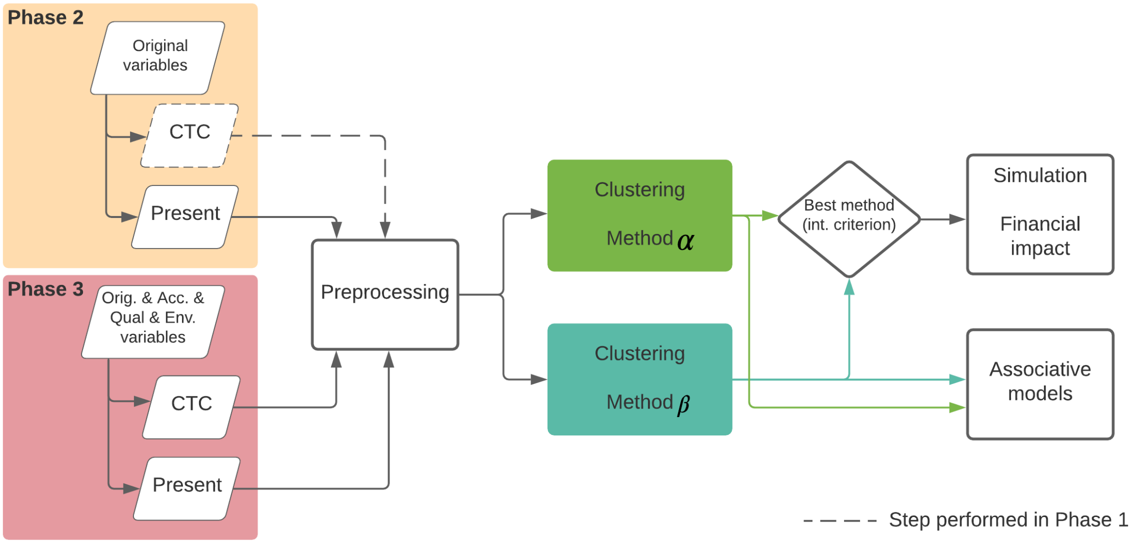

Figure 4.5: Scheme of the phase 2 and 3 of the proposed methodology. Orig. - Original; Acc. - access; Qual. - quality; env. - environmental; Hier. clust. - Hierarchical clustering; int. - internal

of the subsets are studied.

Phase 3 applies the same methodological of the precedent phase, however uses the data sets that cover the original variables and the access, quality and environmental features. The impact on the funding provoke by the implementation of the novel groupings was studied for both scenarios.

4.4.2.A Interpretability of results — Decision Trees

The step of dimensionality reduction of the data sets in the preprocessing pipeline caused the loss of the interpretability, as the strategy implemented was PCA. To recover this important aspect for the discussion a decision tree tool was implemented. This algorithm is a supervised learning approach. It is currently one of the most used computational methods for classification tasks. Since it handles continuous and categorical features, generates models which are understandable and easy to interpret and also indicates the most relevant factors of the data sets to predict/classify (Safavian and Landgrebe, 1991).

This algorithm requires the adjustment of its hyperparameters so that the model architecture is suitable for the considered data. The splitting criterion, the splitting strategy and the maximum depth of the tree make up the set of the principal hyperparameters of this method (Mantovani et al., 2018). The splitting criterion chosen was the entropy for measuring the information gained. This decision was taken randomly as the literature reports that the results between the main measures (entropy and Gini impurity) only differ in 2% of cases (Raileanu and Stoffel, 2004). Regarding the strategy, it was followed the referred picking the best (instead of the best random split), as the weaknesses that the chosen approach comprises are: more computationally demanding and a higher probability of overfitting. Which for the relatively low size of the data sets and the fact that the motivation for using this machine learning technique makes overfitting an advantage. Once again the motivation was the main factor for deciding the maximum depth. That was defined until all last nodes (leaves of the three) had one label each.

4.4.2.B Evaluation of the financial impact of the novel hospital groups

The effect on the hospital funding was assessed by evaluating the reimbursement of the medical appointments, as they are the line of production of the hospital care which unit price is directly related to the group that the provider belongs to. The consultations unitary price was defined by the minimum unit cost of this service that is found when all the providers of hospital groups are regarded (ACSS, 2012; Ferreira et al., 2019).

The specific costs for consultation were not available. For this reason, an approximated model was formulated using the cost for each health care unit of an equivalent patient.[8] The most recent values available are from 2017. Hence the analysis for the Present scenario is done considering this year.

First, it was selected the hospital of each class with the lowest cost per equivalent patient in the year of 2013, the year in which the current rules for funding the hospital were introduced and the prices were defined (ACSS, 2012). For each of the selected provider, the proportion of the unit consultation price applied in 2013 to the respective group over the unitary cost of the equivalent patient was computed. Consequently, four values were obtained: 1.560%, 1.793%, 2.888% and 2.989% corresponding respectively to the current classes B, C, D and E.

Then, it was assumed that hospitals which are placed in the same category have similar behaviour regarding costs since the clustering process was performed with variables that could explain the expenditure of the healthcare units. Ergo, it is considered that the healthcare units of the same class share the same proportion of medical consultations cost over the total cost of an equivalent patient. Thus, the unitary cost of consultations was determined by multiplying the coefficient mentioned in the previous paragraph with the contemporary unitary cost of the standard patient.

Four cases were studied. These are the combinations generated for the pair of scenarios covered in the project (CTC and Present) regarding the different set of features that were analysed: only the original set and the one that contemplates not only the original but additionally the quality, access and the environmental aspects.

Two final notes: it is used the grouping that is proposed by the method that had the highest silhouette value and the provider CHO is not included in the analysis because of the not availability of the expenditure data regarding this provider.

4.4.3 Acquisition and integration of data

Figure 4.6 illustrates the preparation of the data collected from different sources and formats, so that all the information could be integrated into a single data set. The process is comprised of two parts.

Part 1 comprises a pipeline of four processes, which are applied for every file that is extracted from any source. The initial files used in this work encompassed .pdf, .xlsv and .csv formats. Part 2 is executed when all the files that cover the totality of variables of a data set (a specific type of variables for

[8] `https://benchmarking-acss.min-saude.pt/BH_EconFinDashboard` accessed on 07/09/2020

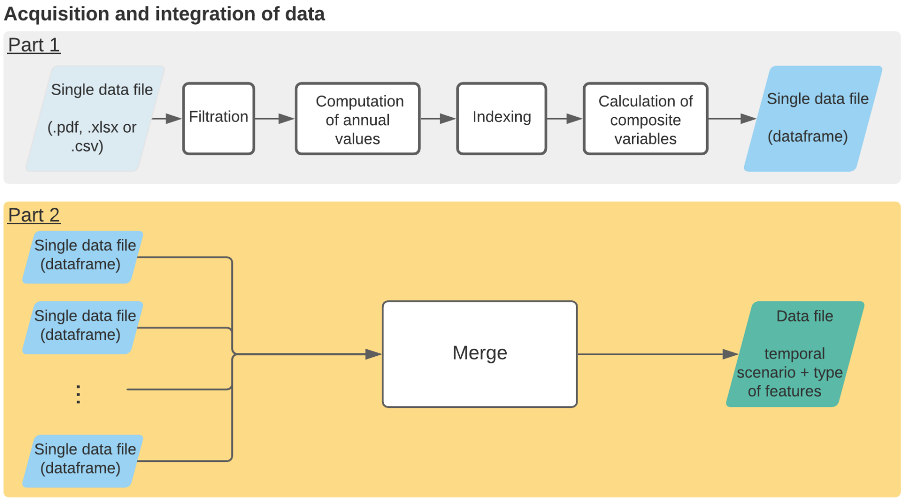

Figure 4.6: Framework regarding the acquisition and integration of the data

a certain scenario) have been submitted to part 1. This second step generates the data set that is used in phases 1, 2 and 3.

First, the raw data is filtrated so that the data only includes information with respect to the healthcare units under the scope of the work, presented in Section 4.1. Second, it is ensured that all the variables regard the annual values. This is achieved by computing the arithmetic average for those variables that do not are expressed in this time frame. Third, due to the variety of sources used different terminologies are found to identify a single healthcare unit, an uniformisation of the terms occurs. This consist of attributing a unique index for each provider. Fourth, all the computations necessary for the definition of the composite variables are performed here. Since there are a few variables that require extra calculations that involve more than one feature collected.

Part 2 consist simply on the merging of all the different files regarding a case. So that the data set can be used in the mainframe of the practical work: phases 1 to 3, as described in Section 4.4.

4.4.4 Preprocessing pipeline

Preprocessing pipeline is illustrated in Figure 4.7. This process is necessary to ensure that data sets comply with all requirements of the machine learning algorithms. To achieve this outcome several steps are contemplated. Section 4.4.4.A details the procedure followed to address the challenges raised by categorical variables, since clustering algorithms are not able to deal with these type of features. Section 4.4.4.B outlines the process for handling missing information. Section 4.4.4.C describes the procedure to handle the different scales used, which unsolved can generate miss-leading results. Lastly, Section 4.4.4.D explains the approach for dealing with strongly correlated variables, which can lead to aggregation based on unbalanced perspectives.

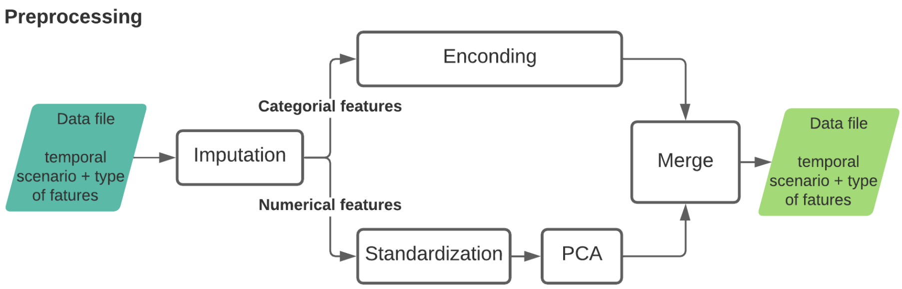

Figure 4.7: Preprocessing pipeline

4.4.4.A Dealing with categorical variables — Encoding

There are characteristics of healthcare units that have a qualitative nature. As previously introduced at the beginning of Chapter 3, these correspond to categorical variables. This type of features has two ramifications: categorical ordinals and categorical non-ordinal variables. The ordinals have several nominal values that can assumed and that are ordered. For instance the type of urgency of a hospital. It can be ordered in terms of complexity and costs (SUB, SUMC and SUP). However, it is possible that the spacing between categories may not be homogeneous. The non-ordinal contemplates the features that can have different categories, but that no intrinsic order exists intrinsic to the data described.

The work covers a total of three categorical features: urgency typology, university hospital and hospital categorization. All these features are ordinal. A decision was made to handle them as non-ordinal features, due to lack of information on the matter which prevents the making of a well-founded decision concerning the distance between each possible value. Thus the process of encoding the categorical features, which is the conversion of categorical variables into numerical. So that the clustering method can be properly implemented.

All the aforementioned categorical variables were submitted to the dummification process. This method converts all the submitted features into binary variables. This definition is concerning the number of conditions that each variable can assume. For example, considering the urgency typology and university hospital. The former feature has three options (SUB, SUMC and SUP) and the latter has solely two (be or not be). Therefore, the university hospital is termed binary and the urgency typology as a non-binary. The non-binary requires the manipulation of the weights of the numerical variables created by the encoding process, so the information of this original counts as just one feature, rather the three that are replacing it in the data set - due to the encoding. Thus, for these particulars three features, the weight attributed to these features is 1/3.

4.4.4.B Dealing with missing values — Imputation

There are missing values in the sets of original, access and quality features. Therefore, imputation methods are applied to these data sets. This type of methods are techniques that replaced the missing values.

First, regarding the original features described in Section 4.3.1. There are two slightly different sets: one used for the CTC scenario and one for the Present scenario. Focusing first in the CTC scenario. There are missing values in the features: psychiatric urgencies (27/28 - 96% hospitals lacking information); pediatric urgency (2/28 - 7%); obstetric urgency (4/28 - 14%); CDTT internal (1/28 - 3.5%) ; CDTT external (1/28 - 3.5%). To deal with those absent values different actions were taken, depending on the ratio between known/unknown for each particular variable. Following the same order of the presentation of the features presented in this paragraph, the procedures implemented were: replacing missing values by zero - for the first three mentioned variables and application of imputation by k-NN technique for which k is equal to 2.

The data collected on Present scenario lacks information in CDTT internal (18/28 - 64%), CDTT external (22/28 - 78.5%) and CDTT total (17/28 - 61%). The imputation process for these values was performed according to the equation 4.1.

$$CDTT_{tj\text{Present scenario}} = \text{CDTT}_{tj\text{CTC scenario}} \times \text{growth rate of total CDTT} \tag{4.1}$$

In equation 4.1, *t* correspond to the type of feature type total, internal, external, and *j* is the hospital from the set of 28 hospitals for which the value is unknown that are studied.

Second, access variables solely have missing values regarding the CHO in CTC scenario. These missing values were substituted with the results of applying the K-NN imputation method with the k = 2, for which the data set will include not only the access variables but also the original ones.

Third, quality features also contained missing values on both scenarios. Regarding the CTC scenario, again the CHO has missing values for all the variables of the quality set. Additionally, there were also a few variables which presented incomplete data: a couple of features in respect to birth complications (both with 2/28 - 7% hospitals lacking information), and the pressure ulcer rate (1/28 - 3.5%). For all of these, it was implemented the procedure of K-NN imputation with k=2. It is important to make a remark concerning the imputation technique of K-NN. It was considered equal weight for all of the features. Since it is assumed that being this a procedure precedent to clustering all factor have equal importance.

4.4.4.C Standardization

A multitude of features is considered throughout the different analyses conducted. So the data comprises a few different scales being used. To uniform the scales standardization of the data sets was performed. In specific, for numerical features. The categorical ones only take the value of 0 or 1 (after the encoding step), making this procedure dispensable. This procedure is applied to the data sets before the computation of the distances, therefore contributing positively to the recovery of the real data structure by the clustering algorithms (Milligan and Cooper, 1988).

4.4.4.D Dimensionality reduction

The methodology followed originally has two steps to reduce the dimensionality of the dataset: feature selection and PCA, as depicted in the scheme of Figure 4.3.

Due to the lack of knowledge on the initial mentioned 50 features from which the selection was made, resulting in the 22 known variables, the feature selection is not covered. Solely the PCA was conducted, although here the number of principal components was also not disclosed. Therefore, the PCA was performed in such a way that the components that explain in total 99% of the variability of the data set. The number of components that results for data sets studied are depicted in Table 4.8, with the dimension of the feature-spaces before this procedure showed under brackets.

PCA method was only designed for dealing with the numerical variables, so only the numerical variables were submitted to it (Wold et al., 1987). To the data set that resulted from the PCA the categorical features were added.

Table 4.8: Number of principal components that defined the (number of) numerical features for the cases analysed preserving 99% of the variability of the data

Scenario	Variables	
	Original	Orig. & Acc. & Qual & Env.
CTC	11 (16)	18 (35)
Present	9 (15)	17 (33)

Orig. - Original; Acc. - access; Qual. - quality; env. - environmental.

4.5 Methodological issues

This section summarises the approaches implemented to accommodate the unconformities of the data. First, Section 4.5.1 details the way data sets to handle the transformations in the providers across time. This is followed by the description of the hyperparameterization of BSCAN, which is addressed due to the very high sensibility of this technique regarding parameters defined.

4.5.1 Data samples

Since the hospital grouping was established noteworthy transformations occurred in the healthcare units. On one hand, the fusion of previously independent hospitals units took place, which led to the creation of novel hospital centres, i.e. CHUA. [9] And on the other, separation of preceding hospital centres groups into independent hospitals. This is the case of HSOG. [10] Furthermore, CHUA solely officially become a CH with the status of university teaching hospital in 2017. [11]

[9] Decree-Law no. 69/2013 `https://data.dre.pt/eli/dec-lei/69/2013/05/17/p/dre/pt/htm` accessed on 17/03/2020
[10] Decree-Law no. 177/2015 `https://data.dre.pt/eli/dec-lei/177/2015/08/25/p/dre/pt/html` accessed on 19/03/2020
[11] Decree-Law no. 101/2017 `https://data.dre.pt/eli/dec-lei/101/2017/08/23/p/dre/pt/html` accessed on 18/03/2020

Due to the structural transformations mentioned above adaptions were implemented. The information of the CTC scenario for CHUA, CHO and HSOG providers do not reflect the current reality of the units. For this reason, the data for the CTC scenario with respect to the units that undergo relevant structural transformations was submitted to an extra procedure.

Firstly, regarding CHUA this study considers the sum of both hospitals until they were merged into a single hospital centre, in 2013. [12]

Secondly, this work also considers the data of the CHO preceding its creation (in 2012) as the sum of values of the two units that were integrated into the process: *Centro Hospitalar de Torres Vedras* and *Centro Hospitalar do Oeste Norte*. [13]

Lastly, in opposition to the pair of cases aforementioned, this provider derives from a division of a Hospital centre into two independent hospitals. The already extincted provider, *Centro Hospitalar Alto Ave (CHAA)*, gave origin to the HSOG and to the *Hospital de São José - Fafe (HSJF)* in 2015 [14]. The latter was transferred to the *Santa casa da Miserircódia de Fafe*, under the regulation of the Decree-Law no.138/2013.[15] Consequently, it was intended to adopt the values of the data collected in the CTC scenario of the CHAA, by multiplying a coefficient that translated the portion of activity of CHAA that was performed by the unit of HSOG. Although, surprisingly the total medical and surgical activity of the last year of the CHAA is very similar to the one performed by solely the HSOG, after the desegregation of this provider from the HSJF. Regarding the external medical appointments reach a value of 255 580 in 2014, produced by the CHAA, and in 2015, was 256 177 only produced by HSOG.[16] This corresponded to an increase of 0.23%. The programmed surgical activity totalized 12 103 in 2014 (CHAA) and 11 573 in 2015 (only the HSOG). It was observed a decrease of 4.37%. [17] From these numbers, it was inferred that the unit HSOG facing the dissociation of the HSJF grew to compensate for the loss of the unit, becoming very similar to the original hospital centre. Therefore no adaption was required.

4.5.2 Clustering hyperparameterization

DBSCAN is a technique that is particularly sensitive to the parameters. Hence the particular focus in the hyperparametrization of this method.

DBSCAN algorithm has three fundamental hyperparameters: 1) distance function; 2) ε - the maximum distance between two samples to belonging to the same neighbourhood, 3) minimum samples - the number of data points in a neighbourhood to be considered a core point.

The hyperparameterization of this clustering method was defined by searching for the combination of parameters which maximized the external validation criterion. The values of the parameters which optimize the quality of the generated clusters are presented in Table 4.9.

[12] Decree-Law no. 69/2013 `https://data.dre.pt/eli/dec-lei/69/2013/05/17/p/dre/pt/htm` accessed on 17/03/2020
[13] Decree no. 276/2012 `https://data.dre.pt/eli/port/276/2012/09/12/p/dre/pt/html` accessed on 18/03/2020
[14] Decree-Law no. 177/2015 `https://data.dre.pt/eli/dec-lei/177/2015/08/25/p/dre/pt/html` accessed on 19/03/2020
[15] Decree-Law no.138/2013 `https://data.dre.pt/eli/dec-lei/138/2013/10/09/p/dre/pt/html` accessed on 20/03/2020
[16] Transparency Portal - hospital medical appointments `https://transparencia.sns.gov.pt/explore/dataset/01_sica_evolucao-mensal-das-consultas-medicas-hospitalares/` accessed on 21/03/2020
[17] Transparency Portal - Surgical procedures `https://transparencia.sns.gov.pt/explore/dataset/01_sica_evolucao-mensal-das-consultas-medicas-hospitalares/` accessed on 21/03/2020

Table 4.9: Optimal parameters for DBSCAN algorithm regarding the CTC scenario and original features

Combination ID	Algorithm	Metric	ε	Min Samples
17	DBSCAN	Man.	4.25	5
18		Euc.	1.5	1
19		Euc. + Ham.	1.5	2
20		Man. + Ham.	4.25	1

ID - [Methodology] Identification number; Man. - Manhattan; Euc. - Euclidean; Euc. + Ham. - Euclidean for numerical features and Hamming for categorical; Man. + Ham. - Manhattan for numerical features and Hamming for categorical

There are a couple of remarks that is important to address concerning this clustering method. Firstly, it has the particularity of being able to consider the data points of a sample as outliers. Thus, for computing the external criterion the data objects classified as outliers were considered as just being a singleton cluster.

Secondly, as there is the possibility of DBSCAN to classify a sample as an outlier, adaptations of the internal criterion are required. As due to this unique characteristic among all the clustering algorithms tested this value can indicate a higher artificial of the performance. For avoiding this situation for the silhouette computation the outliers will not be considered. This procedure makes it not straightforward the comparison of silhouette results of the DBSCAN with the other methods.

Chapter 5

Results

In this chapter, the obtained experimental results are presented. Section 5.1 shows the resulted groups from the three phases of the experimental work. Section 5.2 depicts the financial impact that would be generated as a consequence of the implementation the novel hospital groupings described in the preceding section. Finally, Section 5.3 outlines the evolution in the recent years of the costs, quality and access of the healthcare services concerning the providers covered in this study.

5.1 Clustering

First is depicted the relevant results for the first phase of the work. Followed by those with respect to Phase 2 and 3.

5.1.1 Phase 1: Testing different clustering methodologies for the original features in the CTC scenario

Figure 5.1 shows the within-cluster sum of squares (WCSS) according to the hyperparameter of K-means algorithm. This was performed for all the four similarity metrics tested. The plotting of these results is important hence it indicates the optimal number of clusters that best fits the instances studied, based on the elbow method (Shi et al., 2020).

K-means is a non-deterministic algorithm, as opposed to the others techniques listed in Table 4.7. Consequently the results obtained can be slightly different when the exact same hyperparameters and data set are used. To face this issue the WCSS graphics are not solely the result of one single run, rather they depicted all the values of 30 runs. Each point corresponds to the average value and the perpendicular line that appears on certain points reflect the variation around the mean.

From the analysis of Figure 5.1 according to the elbow method, five is identified as the optimal number, since it presents a very pronounce behaviour characteristic of elbow points on the Euclidean and Hamming metric. The analysis covers the cases for aggregation of the providers into four and five groups, as four is the number of categories that currently the units under scope are classified.

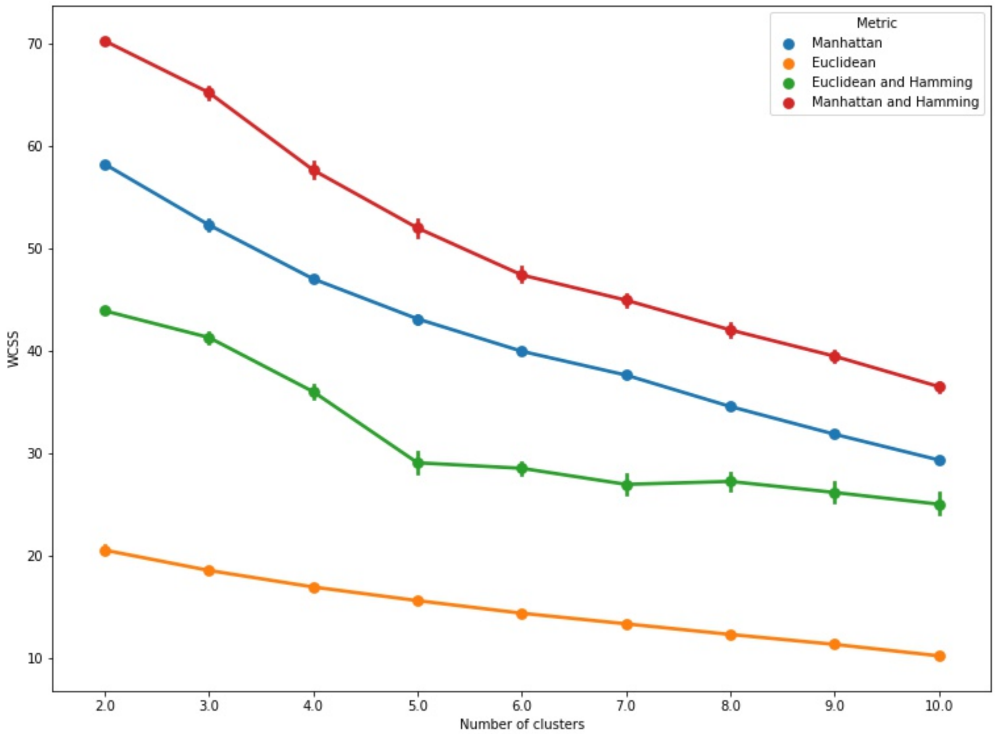

Figure 5.1: Within-cluster sum of squares (WCSS) of the results of applying k-means for the similarity metrics used.

Table 5.1 and Table 5.2 reveal the results of the different clustering combination utilized, for k = 4 and k = 5, respectively. These charts express the number of clusters considered for the target hospitals and also show the corresponding values for each combinations on both the internal and external validation criteria. Moreover, these tables indicate the couple features, numerical and categorical, which best predict the aggregation of the hospitals in subsets. Furthermore, these tables include the assessment of the statistical significance regarding the obtained clusters for each of the methods tested.

As stated above, K-means is a non-deterministic method. Therefore, a different approach ought to be followed for obtaining and analysing the outputs of this method. The aggregation of the K-means algorithms considered in Table 5.1 and Table 5.2 are the best evaluation on the external criterion. For each combination the model was ran 30 times.

The results generated by the 20 tested methodologies are presented in Tables 5.1, 5.2 and 5.3. By observing the values on external and internal criteria depicted in these tables, the clusters with the best performance with respect to the the internal and external criterion can be identified. These are *ID 10* - Hierarchical with the Ward's linkage criterion - for k=4 (having a silhouette score of 0.359867) and *ID2* - K-means with Euclidean metric - for k=5 (with a value of 0.571429 for the adjusted Rand index), respectively. Hence this two are the methodologies utilized in the clustering tasks that are subsequently presented in this document, corresponding to the method α and β in both Figure 4.4 and Figure 4.5.

Table 5.1: Results from the application of the different tested combination to the data with the original variables, with the number of clusters = 4

ID	External criterion Adjusted Rand index	Internal criterion Silhouette	Strongest Predictor Numerical	Categorical	Statistical significance*
1	0.414105	0.226048	University hospital	Total CDTT	Y
2	**0.500339**	0.189837	University hospital	CMI surgical ambulatory	Y
3	0.327473	0.286912	University hospital	Nurses	Y
4	0.389907	0.160098	University hospital	Nurses	Y
5	0.294630	0.285205	University hospital	Nurses	Y
6	0.155445	0.318714	University hospital	Nurses	Y
7	0.296089	0.288527	Urgency Type - SUP	Urgency Type - SUP	Y
8	0.255639	0.228400	University hospital	Nurses	Y
9	**0.495659**	0.212423	Urgency Type - SUP	Urgency Type - SUP	Y
10	0.199359	**0.359867**	University hospital	Nurses	Y
11	0.363173	0.271526	Urgency Type - SUP	Urgency Type - SUP	Y
12	0.323193	0.226890	University hospital	Total CDTT	Y
13	0.224670	0.225269	University hospital	University hospital	Y
14	0.175908	0.230770	University hospital	Nurses	Y
15	0.149091	0.169891	University hospital	Nurses	Y
16	0.121951	0.225910	University hospital	Nurses	Y

ID - [Methodology] Identification number; Groups P-values < 0.01; Y - Yes;

Table 5.2: Results from the application of the different tested combination to the data with the original variables, with the number of clusters = 5

ID	External criterion Adjusted Rand index	Internal criterion Silhouette	Strongest Predictor Numerical	Categorical	Statistical significance*
1	0.432979	0.185248	University hospital	CMI surgical hospitalization	Y
2	**0.571429**	0.134417	University hospital	Urgency Type - SUP	Y
3	0.368421	0.190092	Urgency Type - SUP	Nurses	Y
4	0.353705	0.190593	University hospital	Nurses	Y
5	0.286344	0.265503	University hospital	Nurses	Y
6	0.213758	**0.346319**	University hospital	Nurses	Y
7	0.293233	0.280614	Urgency Type - SUP	Urgency Type - SUMC	Y
8	0.276382	0.229677	University hospital	Nurses	Y
9	0.455206	0.219007	University hospital	Urgency Type - SUP	Y
10	0.213758	**0.346319**	University hospital	Nurses	Y
11	0.363533	0.271466	Urgency Type - SUP	Urgency Type - SUP	Y
12	0.322908	0.211125	University hospital	Nurses	Y
13	0.197044	0.177740	University hospital	Nurses	Y
14	0.147783	0.212554	University hospital	Nurses	Y
15	0.197044	0.119127	University hospital	Nurses	Y
16	0.169086	0.193322	University hospital	Operation rooms	Y

ID - [Methodology] Identification number; Groups P-values < 0.01; Y - Yes;

Table 5.3: Results from the application of the DBSCAN algorithm to the data with the original variables

ID	Number of clusters	External criterion Adjusted Rand index	Internal criterion Silhouette	Strongest Predictor Numerical	Categorical	Statistical significance
17	19.0	0.296142	0.069851	University hospital[1]	Beds in specialized units	Y
18	19.0	0.296142	0.069851	University hospital[1]	Beds in specialized units	Y
19	19.0	0.296142	0.069851	University hospital[1]	Beds in specialized units	Y
20	19.0	0.296142	0.069851	University hospital[1]	Beds in specialized units	Y

* ID - [Methodology] Identification number;
* Groups P-values < 0.01. Y - Yes;
[1] It is not statistically significantly. See table A.6.

The output of the hierarchical clustering presents a particular aspect being unique when compared with all the other results. That is the dendrogram produced. Figure 5.2 illustrates the dendrogram for the Present scenario. Note that the range of distance separating the clusters when $K\bar{4}$ is very narrow. This implies that this number of groups is far from being the optimal for the case studied. Hence, it was considered the number of groups to be five. This was the choice considering that this corresponded to the alternative value identified previously as the number for the optimal number of cluster, as stated in the beginning of this subsection.

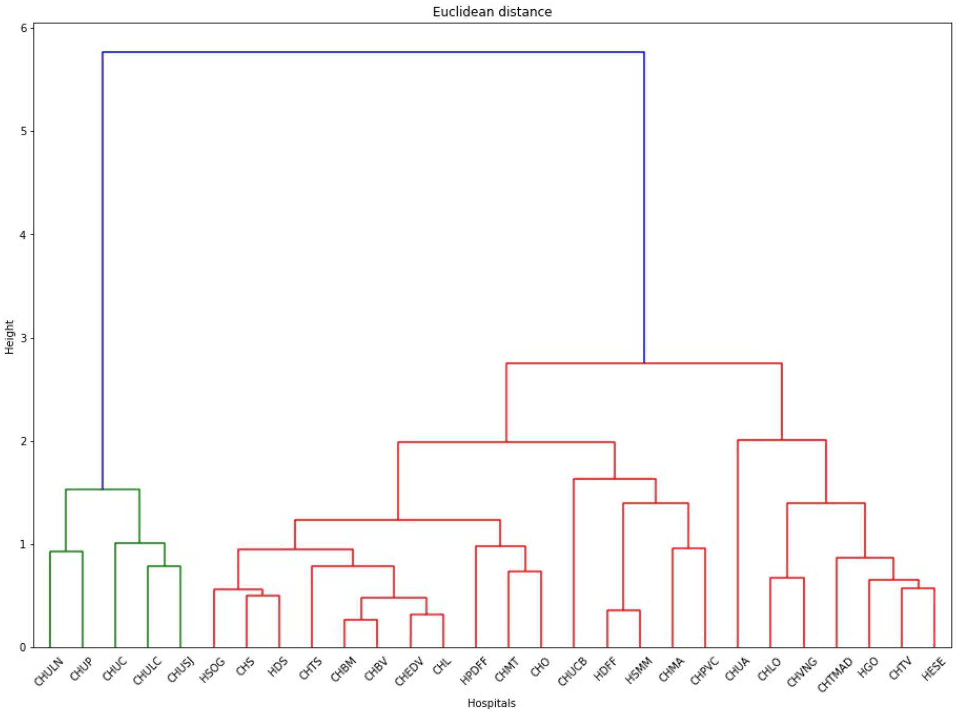

Figure 5.2: Dendrogram produced by the hierarchical clustering method with the Ward's linkage-criterion for the data set comprising the original features in the present scenario.

Figure 5.3 and Figure 5.5 depict how the 28 hospitals in the CTC scenario are separated in homogeneous groups. The equivalent schemes for the Present scenario are Figure 5.7 and Figure 5.8, respectively.

Examining figure 5.3 it is possible to identify the groups created by the hierarchical clustering for the CTC scenario. These features are: nurses, university hospital and operation rooms. This contrasts with those relevant to characterize the classes produced by the K-means technique: beds, urgency episodes, equivalent patients, medical appointments and CMI medical hospitalization, as depicted in Figure 5.5.

Observing Figure 5.7, are extracted the variables that define the hospitals groups with respect to the Present scenario obtained from the hierarchical clustering. These are: hospital categorization (class 1), nurses, equivalent patients and the medical hours. The corresponding decision tree regarding the output of the K-means algorithm for the same scenario is depicted in Figure 5.5. The variables that describe the resulted classes are: urgency type (SUP), medical appointments, hospitalization episodes and the equivalent patients.

5.1.2 Phase 2: Application of the most promised methodology to sample with original features in the Present Scenario

This subsection contemplates the aggregation results of the 28 hospitals units produced in Phase 2 of the experimental framework, which deals with the data sets that described the healthcare providers with the original set of features. Figure 5.6 show the current categorization of the hospitals and the proposed

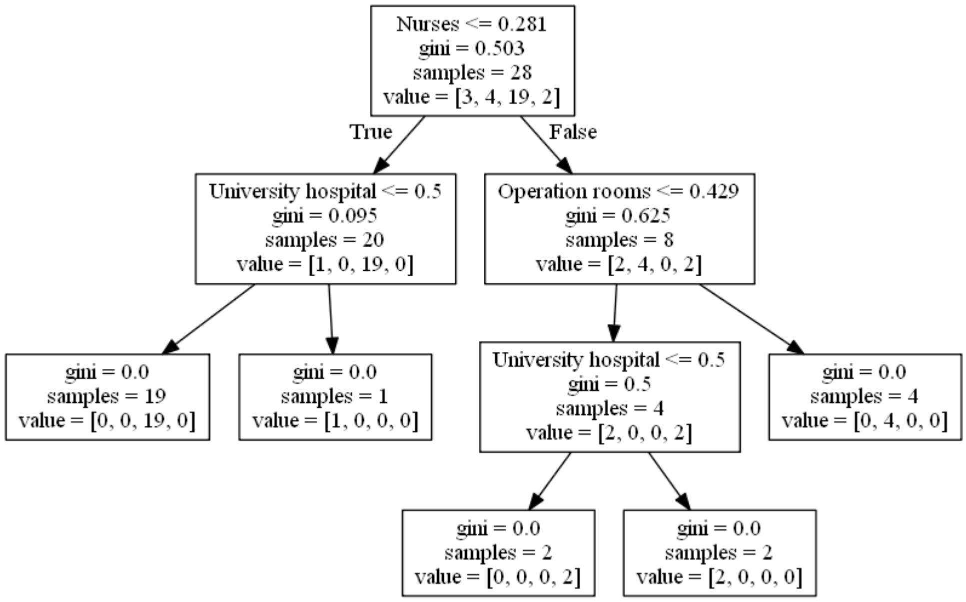

Figure 5.3: Decision tree that results from the hierarchical clustering with Ward's method (k=4) for the sample with original features in the CTC scenario

grouping that results from the method α (hierarchical algorithm) and method β (K-means), referred in the previous subsection. Figure 5.7 and Figure 5.8 illustrate the associative models that describe the subsets produced by the hierarchical algorithm and K-means method concerning the Present scenario under Phase 2.

Table 5.4 depicts the validation assessment of the clustering results concerning the Present scenario of Phase 2. It also cover the statistical significance of these results.

Table 5.4: Validation and statistical significance of the clusters produced in Present scenario of Phase 2

Clustering method	**External criterion** Adjusted Rand index	**Internal criterion** Silhouette	**Statistical significance** *
K-means	0.5517886	0.2580752	Y
Hierarchical clustering	0.5859564	0.2534862	Y

* Groups P-values < 0.01. Y - Yes;

5.1.3 Phase 3: Application of the most promised methodology to sample with original, quality, access and environmental features

In this subsection are presented the obtained results from the application of the selected methods to the data set with all the set of variables described in previous chapter: not only the production and capacity of the healthcare units, but also the quality, access and environmental factors. Figure 5.9 and Figure 5.12 illustrate the novel grouping proposed for CTC scenario and Present scenario, respectively.

Figure 5.10 and Figure 5.11 correspond respectively to the decision trees regarding the results generated by the hierarchical algorithm and K-means method with regard to the CTC scenario. Finally, Figure 5.13 and Figure 5.14 illustrate the decision trees for Present scenario of the hierarchical algorithm and K-means algorithm, respectively.

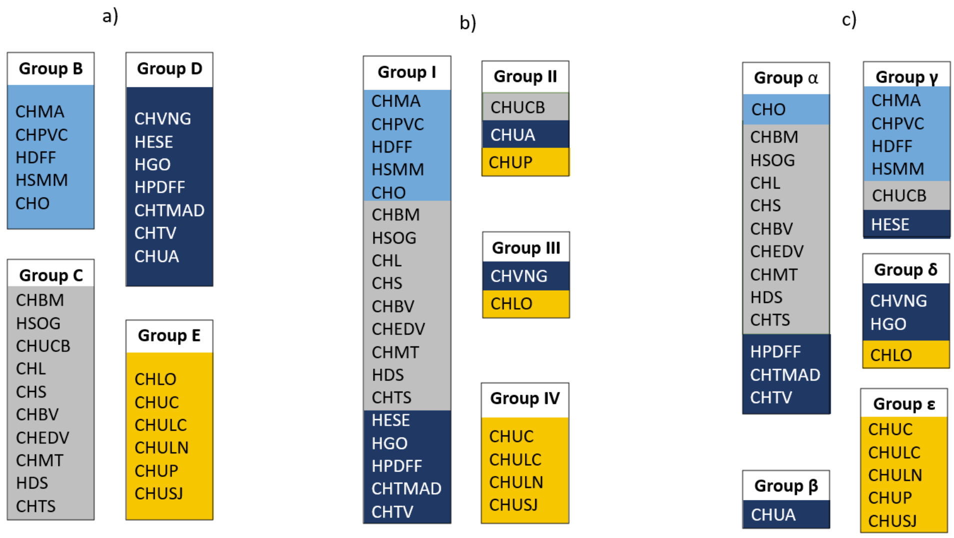

Figure 5.4: Comparison of the novel hospitals clusters obtained by different methods with the data set that comprises the original features in the CTC scenario. a) established groups; b) hierarchical clustering with Ward's criterion (k=4); c) K-means (k=5)

Table 5.5 and Table 5.6 illustrate respectively the assessment regarding the validation and statistical significance of results for the CTC and Present scenario of Phase 3.

5.1.3.A CTC scenario

The figure 5.10 and the figure 5.11 express how are the 28 hospitals under scope being actually separated into groups in the CTC scenario. And the figure 5.13 and the figure 5.14, the equivalents for the Present scenario, in the same order.

Firstly, looking to figure 5.10, the variables that identify the groups created by the hierarchical clustering method for the CTC are: two environmental features (proportion of the population with the 2nd cycle level and the purchase power), one quality variable (complications with non-instrumented vaginal births) and one belonging to the original set (Total CDTT). Both the environmental and original features identified for the hierarchical clustering algorithm are also relevant for the K-means case. There are a couple of other factors that are required to be included in this case: longevity index (environmental variable) and CMI surgical ambulatory (original variable), as depicted in figure 5.11.

Table 5.5: Validation and statistical significance of the clusters produced in CTC scenario of Phase 3

Clustering method	**External criterion** Adjusted Rand index	**Internal criterion** Silhouette	**Statistical significance** *
K-means	0.2448588	0.1827968	Y
Hierarchical clustering	0.2184401	0.1897999	Y

* Groups P-values < 0.01. Y - Yes;

5.1.3.B Present Scenario

In the Present scenario for the hierarchical clustering three variables can characterize the hospital classes for this situation. These are: higher education and residence population (environmental fac-

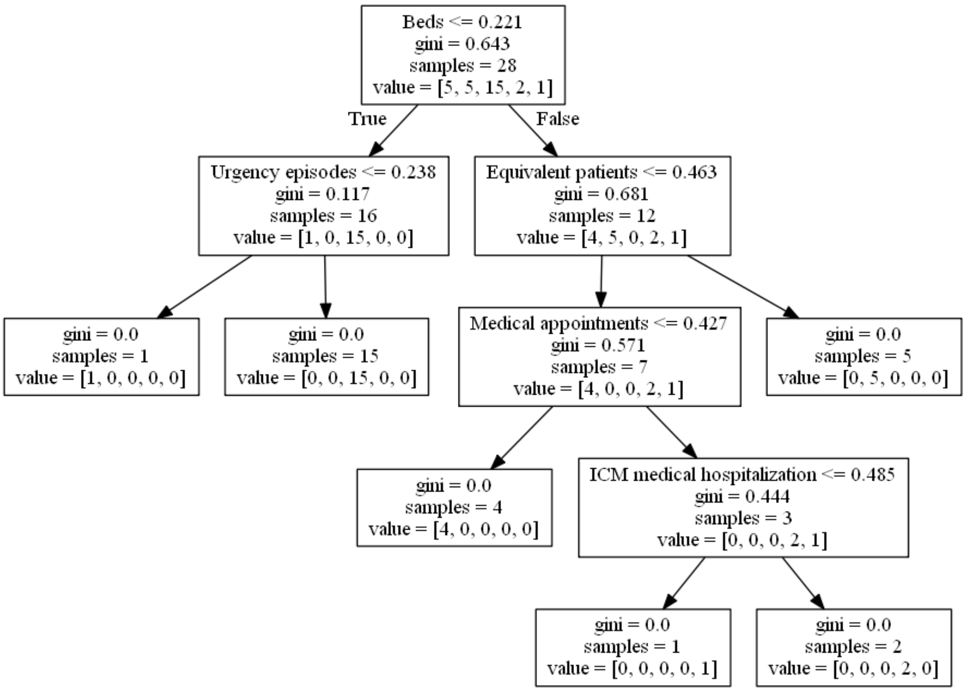

Figure 5.5: Decision tree that results from the K-means (k=5) for the sample with original features in the CTC scenario

tors) and one original feature, the medical appointments, as it is observed in Figure 5.13. The other result that uses the same data set but with the other computational approach has one environmental (purchase power), one access feature (consultations in appropriate time) and two original variables (Beds in specialized units and total CDTT), as shown by Figure 5.14.

Table 5.6: Validation and statistical significance of the clusters produced in Present scenario of Phase 3

Clustering method	**External criterion** Adjusted Rand index	**Internal criterion** Silhouette	**Statistical significance** *
K-means	0.3339658	0.2162918	Y
Hierarchical clustering	0.1533101	0.3042909	Y

* Groups P-values < 0.01. Y - Yes;

5.2 Evaluation of the financial impact of the novel hospital groups

The table 5.7 presents the financial effect on the hospital budget that results from considering the novel grouping. The values showed in this table correspond to the calculation of the expression 5.1.

$$\text{Expenditure}_{\text{novel hospital grouping}} - \text{Expenditure}_{\text{ACSS hospital grouping}} \tag{5.1}$$

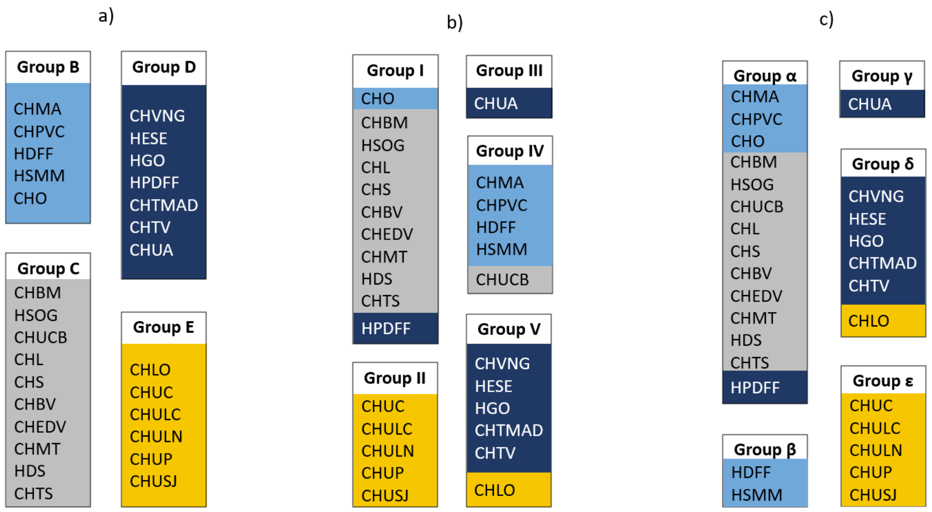

Figure 5.6: Comparison of the novel hospitals clusters obtained by different methods with the data set that comprises the original features in the Present scenario. a) established groups; b) hierarchical clustering with Ward's criterion (k=4); c) K-means (k=5)

Table 5.7: Financial impact on the reimbursement of medical appointments for both the temporal scenarios considered as consequence of the implementation of the novel proposed groups

	CTC Scenario - Year 2013		Present Scenario - year 2017	
Set of variables	Absolute value	Relative	Absolute value	Relative
Original features	-14 623 927 €	-10.19%	+110 794 012 €	+ 20.26%
Orig. + acc. + qual. + envir. features	-12 864 619 €	-8.97%	+ 59 511 170 €	+ 11.38%

Orig + acc + qual + envir - Original, access, quality and environmental

5.3 Evolution in time of the costs, quality and access of the hospitals

In this section of the work the evolution of the hospitals with respect to three indicators are presented. Each one corresponding to a key factor identified in Section 2.1: efficiency, access and quality of the healthcare services. Figure 5.15, Figure 5.16, Figure 5.17 and Figure 5.18 depicted the values for the ACSS group of hospitals B, C, D and E, respectively.

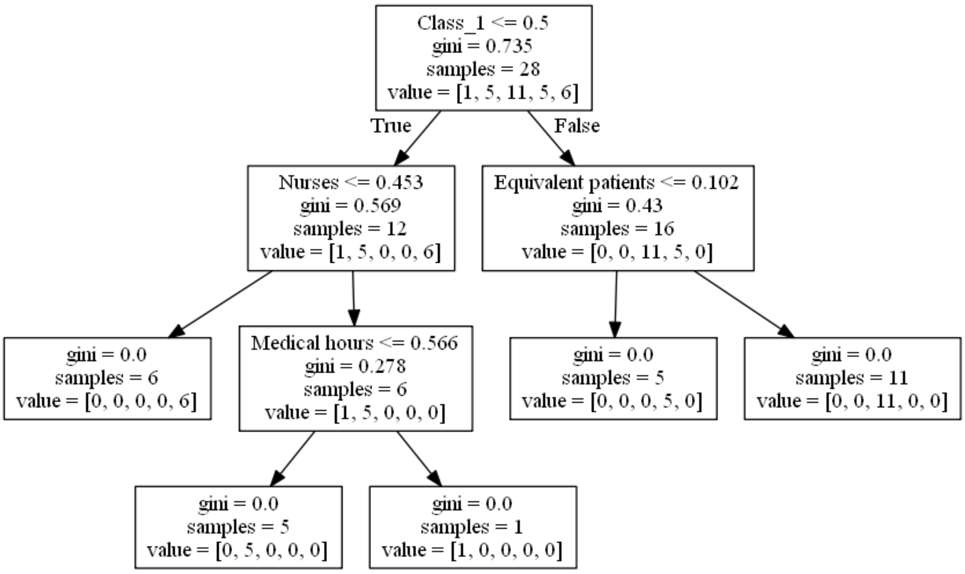

Figure 5.7: Decision tree that results from the hierarchical clustering with Ward's method (k=4) for the sample with original features in the Present scenario

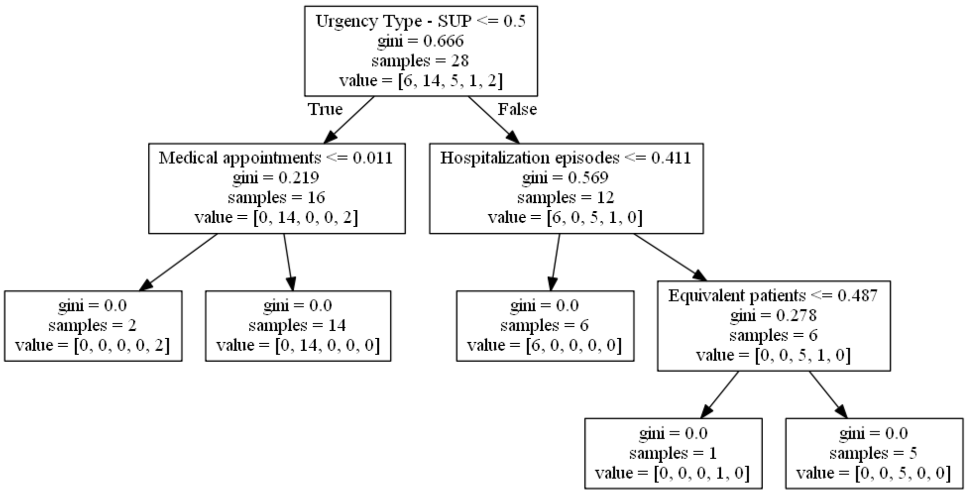

Figure 5.8: Decision tree that results from the K-means (k=5) for the sample with original features in the Present scenario

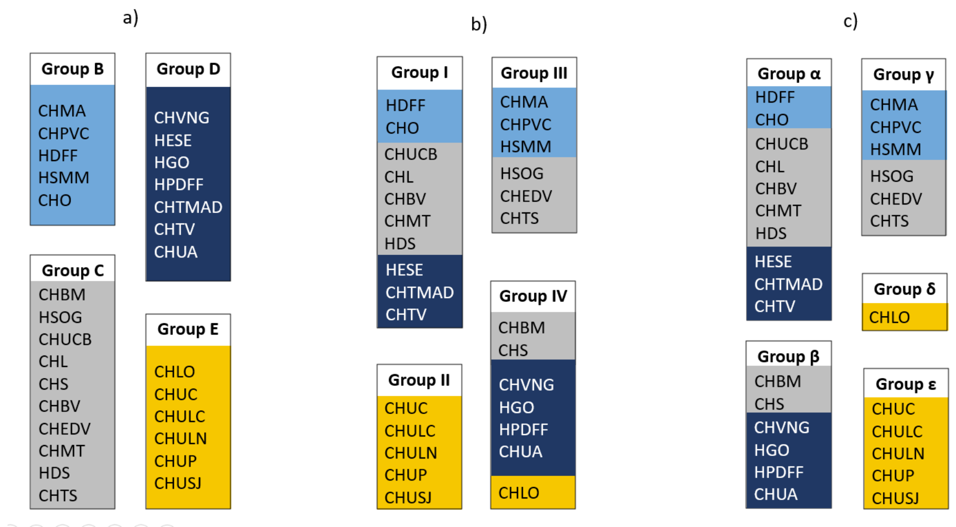

Figure 5.9: Comparison of the novel hospitals clusters obtained by different methods with the data set that comprises the original, quality, access and environmental features in the CTC scenario. a) established groups; b) hierarchical clustering with Ward's criterion (k=5); c) K-means (k=5)

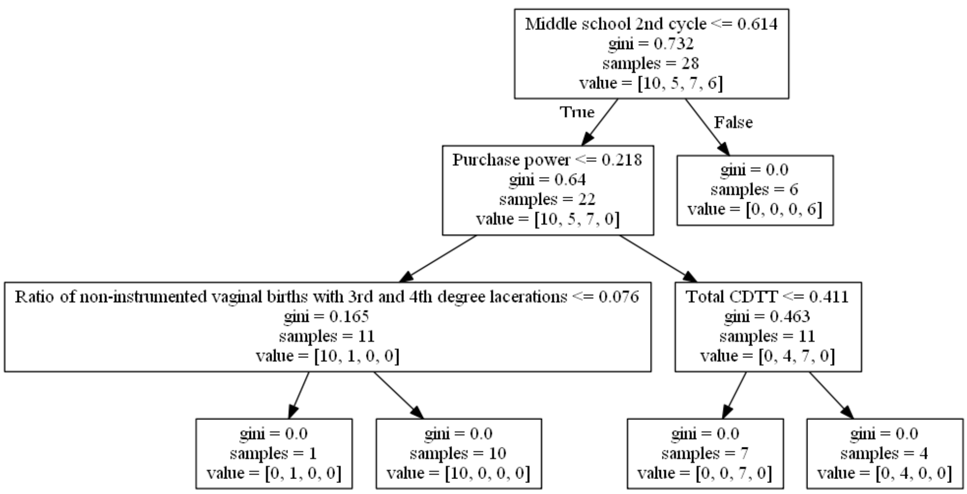

Figure 5.10: Decision tree that results from the hierarchical clustering with Ward's method (k=4) for original, quality, access and environmental features in the CTC scenario

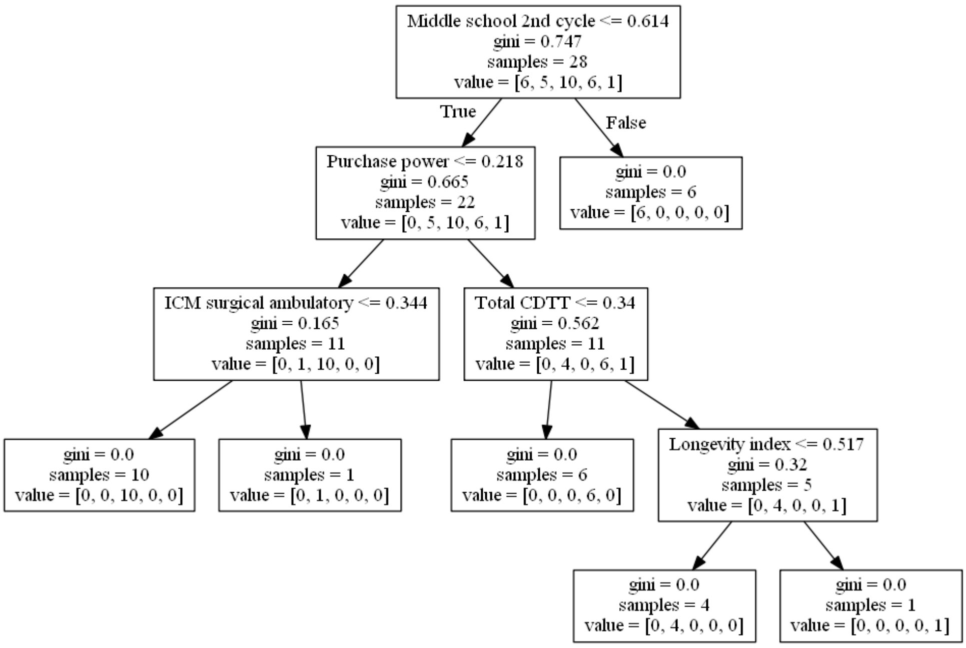

Figure 5.11: Decision tree that results from the hierarchical clustering with K-means (k=5) for original, quality, access and environmental features in the CTC scenario

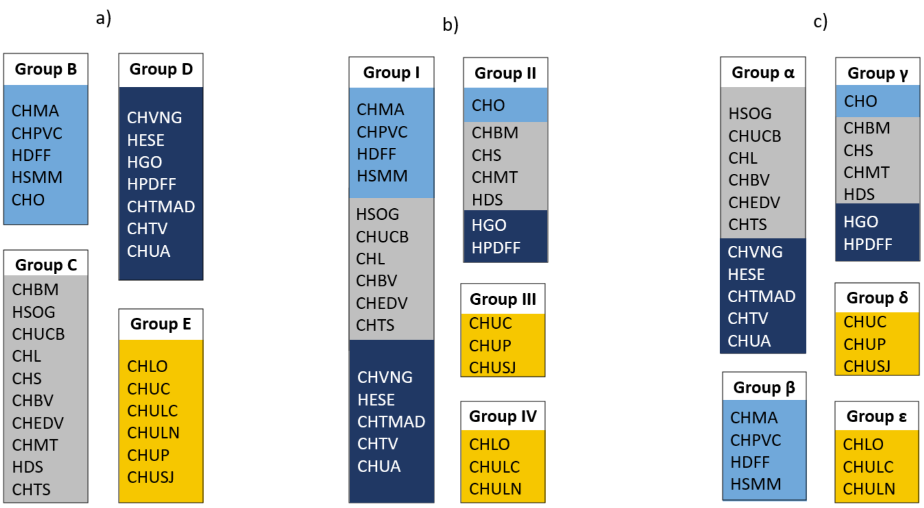

Figure 5.12: Comparison of the novel hospitals clusters obtained by different methods with the data set that comprises the original, quality, access and environmental features in the Present scenario. a) established groups; b) hierarchical clustering with Ward's criterion (k=4); c) K-means (k=5)

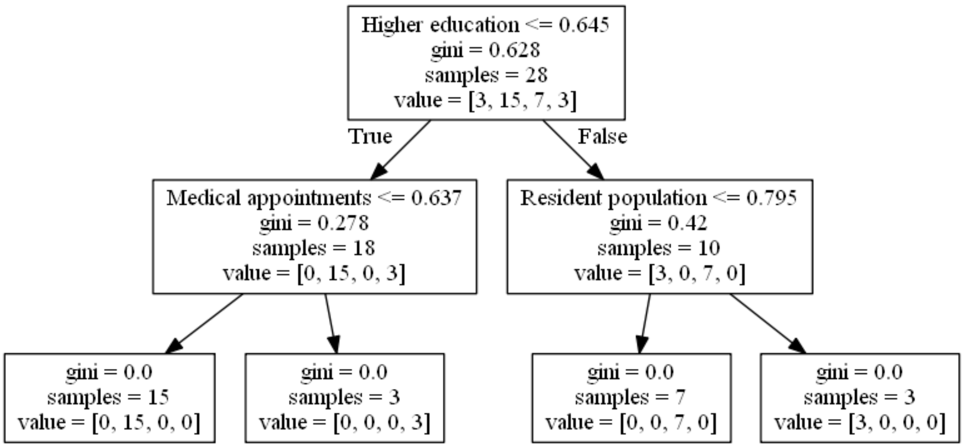

Figure 5.13: Decision tree that results from the hierarchical clustering with Ward's method (k=4) for original, quality, access and environmental features in the Present scenario

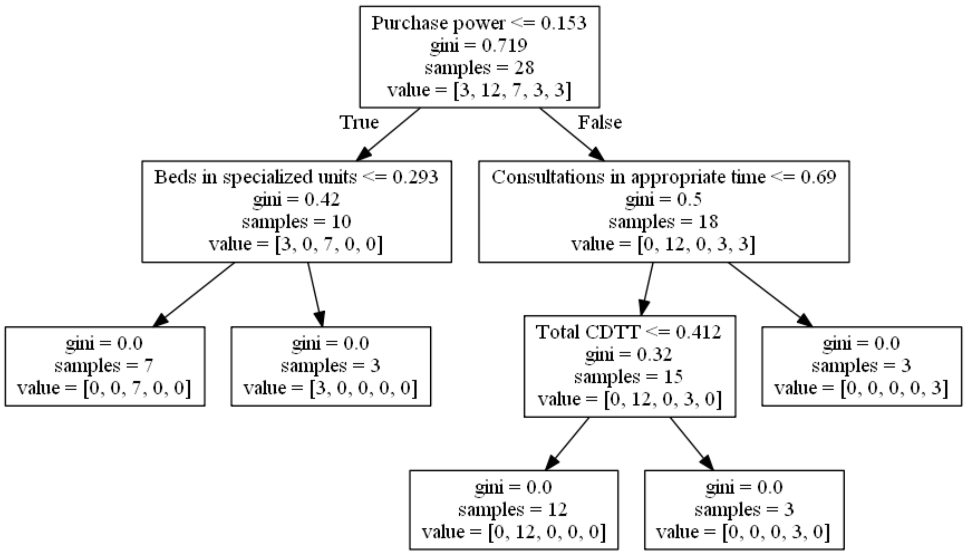

Figure 5.14: Decision tree that results from the hierarchical clustering with k-means (k=5) for original, quality, access and environmental features in the Present scenario

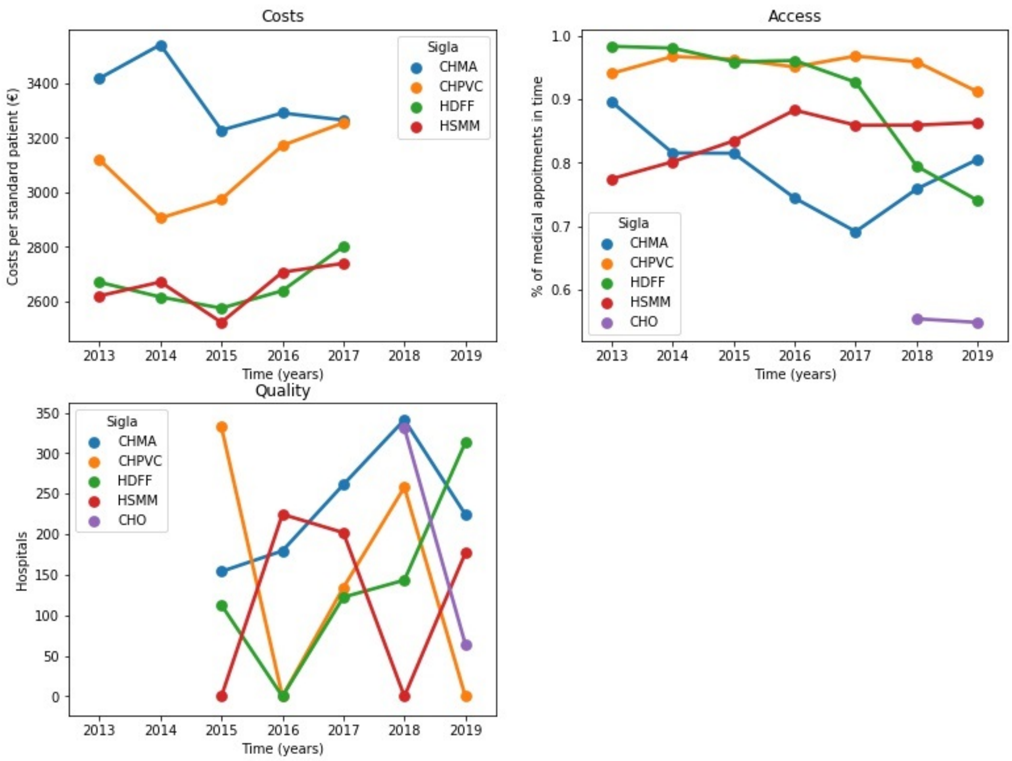

Figure 5.15: Performance of the hospitals of the current group B regarding three indicators: the cost per equivalent patient (upper left); % of medical appointments done in the adequate time (upper right) and, the Sepsis on the post-surgery cases per 100.000 (lower left)

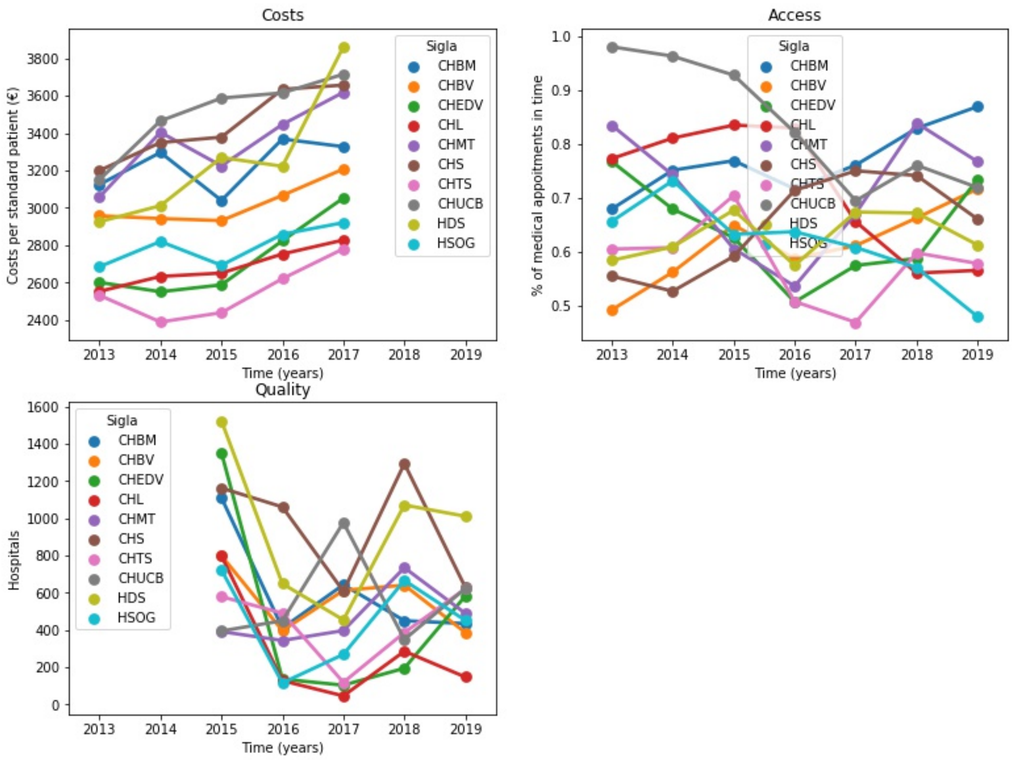

Figure 5.16: Performance of the hospitals of the current group C regarding three indicators: the cost per equivalent patient (upper left); % of medical appointments done in the adequate time (upper right) and, the Sepsis on the post-surgery cases per 100.000 (lower left)

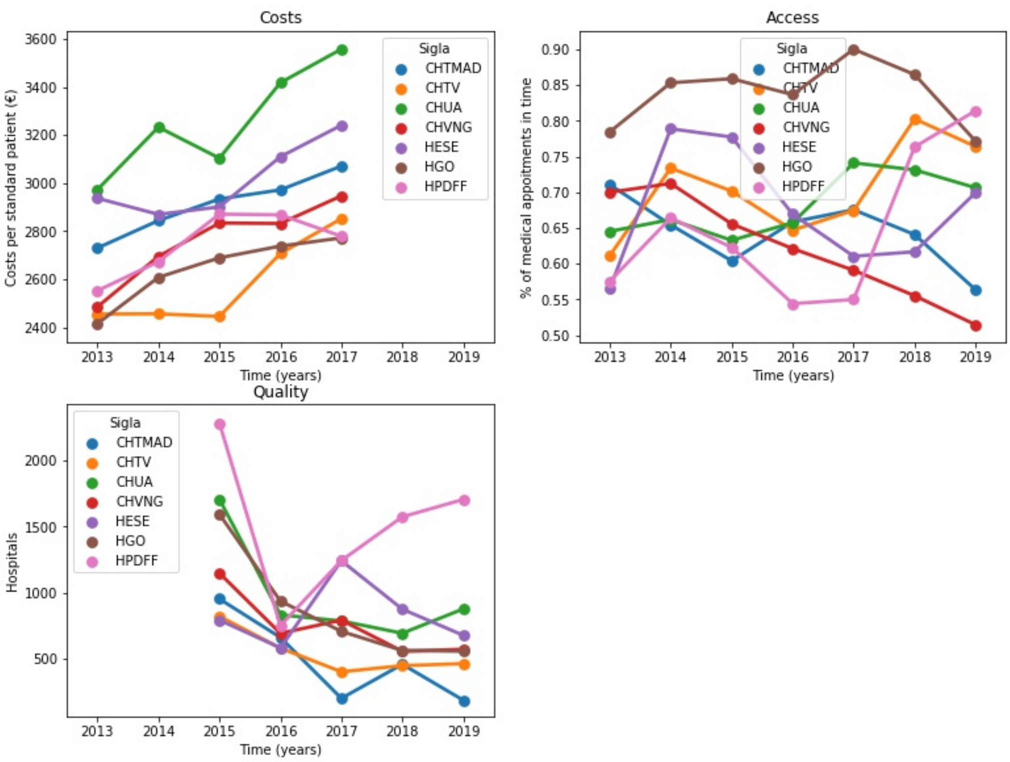

Figure 5.17: Performance of the hospitals of the current group D regarding three indicators: the cost per equivalent patient (upper left); % of medical appointments done in the adequate time (upper right) and, the Sepsis on the post-surgery cases per 100.000 (lower left)

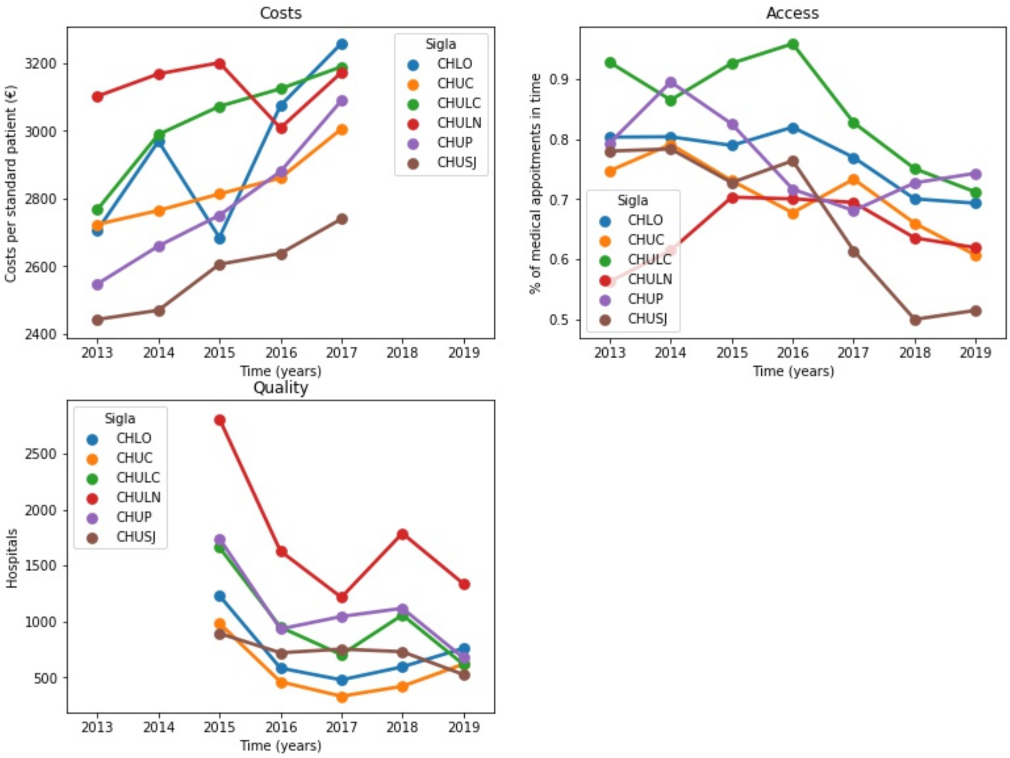

Figure 5.18: Performance of the hospitals of the current group E regarding three indicators: the cost per equivalent patient (upper left); % of medical appointments done in the adequate time (upper right) and, the Sepsis on the post-surgery cases per 100.000 (lower left)

Chapter 6

Discussion

This chapter comprises the discussion of the experimental results depicted in the precedent chapter (Chapter 5). The discussion follows the thread outlined in Section 1.2, in which the objectives are listed. First, Section 6.1 addresses the methodologies that best replicates the established results and best groups the hospitals studied. It is followed by the analysis of the impact of time on the grouping hospitals under the original (replicated) model, in Section 6.2. The third phase of the experimental work investigates the impact of including access, quality and environmental dimensions in the clustering process, covered in Section 6.3. Finally, Section 6.4 focus the potential influence of this work on the political and managerial decisions with respect to the healthcare units analysed.

6.1 Phase 1: Replication of the original model

6.1.1 Best method to replicate the current established groups of public hospitals

The initial challenge of the work was the replication of the model that resulted in the NHS hospital groups. This exercise was conditioned by two major constraints. Both are caused by missing information. One with respect to the similarity metric used and the other with the variables utilized. Ergo, the first goal of the work was to understand if without this data is it possible to replicate the results obtained by ACSS.

The information concerning the similarity measure is absent in all the documents consulted regarding the procedure. As described in Chapter 3 in Section 3.2.2 this parameter impacts the values of distances that are measured between the healthcare units, which consequently affects the formation of the clusters, since these are aggregated based upon the (dis)similarity between the providers.

To address this issue, four measures were tested, as illustrated in Table 4.7. The metrics can be divided into two sets. On one hand, there are the more traditional and simple approaches that consist in applying the same metric to all the data with no respect to the nature of the features (e.g. numerical and categorical). This set encompasses the application of the Euclidean and Manathan distances that are applied to the totally of the variables. On the other hand, there are more sophisticated approaches that measure distances between the objects according to the nature of the features, termed here as composite metrics. This set comprises the application of the Euclidean distance for numerical variables combined with the Hamming for the categorical features. Within this category the composite metric that uses Manhattan distance for the non-categorical variables and again the Hamming for the categorical ones is also included.

The results strongly converge towards the hypothesis that euclidean metric was used in the clustering process that is replicated, since the methods with the best values regarding the internal and external validation criteria implement this distance (see Tables 5.1 and 5.2). These are also supported by the fact the Euclidean distance is one of the most commonly used measure in the literature (Berthold and Höppner, 2016). Furthermore, the packages used for generating the results were implemented with this metric as default, *Scikit-learn* and *SciPy* libraries. [1] [2] [3] Considering above referred we can conclude that this limitation is overcome.

On account of the unavailability of information concerning variables, 12 out of the 22 original features were replaced with others that were considered suitable proxies and that were promptly available. Table 4.1 shows the features chosen for this purpose. A request was sent to the responsible entity (ACSS) to access the missing data. Until now no response has been received. Hence, the study was conducted with proxy variables. Three aspects need to be acknowledged.

Firstly, the data indicates the optimal number of clusters (for the original variables in the CTC scenario) to be of 4 or 5. This value is according the expectations, as the optimal number should coincide with the number of classes that comprise the current groups, which are 4. Note that this factor by itself does not guarantee that the data set is totally suitable, but it is an essential requirement to be met.

Secondly, by analysing Tables 5.1, 5.2 and 5.3 it is possible to conclude that the method that better replicates the established hospital groups is the K-means clustering algorithm with the Euclidean distance metric with k = 5. This affirmation is based upon the fact that from all the 20 combinations of studied methods, this one had the highest value in the external criterion, 0.571429 for the adjusted Rand index. It is acknowledged that the method that enacts the best performance concerning the external criterion, K-means algorithm, does not coincide with the method that was used in the process of generating the ACSS results (ACSS, 2012). The original procedure implemented the hierarchical clustering with Ward's linkage criterion. Despite this discrepancy, it is interesting to note that the tested method that provides the output with the best value according to the internal criterion coincides with the one used in the procedure followed by the ACSS. This can be explained by the differences that do exist between the data sets used in the ACSS process and in this study, due to the impossibility of using same of the utilized variables being.

Thirdly, the units are to a larger extend placed according to the established grouping, as depicted in the components a) and c) of Figure 5.4, which are respectively the currently ACSS groups and the results

[1] Hierarchical clustering algorithms `https://scikit-learn.org/stable/modules/generated/sklearn.cluster.AgglomerativeClustering.html#sklearn.cluster.AgglomerativeClustering` accessed on 22/12/2020

[2] DBSCAN methdo `https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html#sklearn.cluster.DBSCAN` accessed on 22/12/2020

[3] K-Means `https://docs.scipy.org/doc/scipy/reference/generated/scipy.cluster.vq.kmeans.html` accessed on 22/12/2020

that more closely get to those - obtained by the K-means method with k = 5. In a more quantitative view, the units from the category B, C and E are placed together missing only one unit, which corresponds to 80%, 90% and 83.3 % ratio between the hospitals group in the cluster with others members of their groups of the ACSS grouping over the total of units belonging to the group. Whereas, the providers of the established group D only achieve a value of 43% in this ratio. It can be speculated that this group was less homogeneous than all the defined classes. Thus, due to the slight disparity in the distances caused by the use of proxy variables this produced enough changes in the distances between the units, which culminated in the fragmentation of the group in the k-means approach. This hypothesis is supported by the fact that for all the other situations analysed 2 of the hospitals that appear here in a different group from the core group, they appear clustered in the core groups (raising the ratio to 71%).

As a final note, the fact that certain hospitals are not aggregated according to the ACSS classes should not be interpret as the model being wrong. These divergences can be due to differences concerning the clustering algorithm, similarity criterion and/or variables (Yang et al., 2017). The first and second elements can be discarded as responsible, considering the focus of the first phase being on the identification of the methodology that best fits the case study. Even more, when it is taken into account that the pool of tested methods was chosen based upon the state of the art. Thus, the discrepancies are most likely caused by the variables used, as a consequence of the divergences on the features-space. Since there were variables that are represented in our model by proxies, which creates similar variables-space, however not equal.

In light of the above paragraph the answer for the first questions is yes, it is possible to replicate the major structure of the results of ACSS, in spite of the necessary adjustments. Consequently, the model conceived in this work is adequate for the purposed objectives, as it enables the study of the influence of time and the inclusion of the features of access, quality and environment on the hospital grouping. The procedure that generates the closest results of ACSS is the K-means algorithm with Euclidean distances for k = 5.

6.1.2 Best division of the samples according to the nature of the data itself

This section begins by answering directly to the second question of the objectives written in Section 1.2. The method that generates the best separation of the hospital units is the hierarchical clustering algorithm with Ward's linkage criterion. The component b) of Figure 5.4 depicts the grouping that results from applying this approach.

As written in Section 3.2.4.B, internal criterion assesses the quality of the division of the data instances. Observing and comparing these values in Tables 5.1, 5.2 and 5.3 the *ID 10* - Hierarchical clustering with the Ward's linkage criterion - for k = 4 (having a silhouette score of 0.359867) corresponds to the methodology with the best score, which implies that this is the method that generates the output that better groups the hospitals.

It is paramount to take into account that the method that was used in the original procedure coincides with the best method for grouping the healthcare providers with the experiment data set. Moreover, the number of clusters obtained in the best clustering method is 4, which reinforces the hypothesis that the replication of the process was successful, since this is the identical number of classes that are defined in the operation being reproduced.

The values of the silhouette score for all the 20 tested methods assume overall low numbers, see Table 5.1, 5.2 and 5.3. The maximum number on this criterion is 0.359867. This is a value that already implies that clusters have some meaning though not very pronounced, indicating that the healthcare providers under analysis are very distinctive. So any division of the hospitals is not expected to achieve a silhouette value much higher than the maximum number of this study. This raises very relevant questions regarding the adequacy of using the hospital groups obtained by the process that was replicated here, conditioned of course by the information available (both regarding data aspects as methodological issues). These results supports the perspective reported in the Ferreira and Marques (2016) that the hospitals are in fact very heterogeneous and this creates challenges for the implementation of fair funding.

6.2 Phase 2: Impact of time in the replicated model

6.2.1 Application of the methodology to the most recent data available

The analysis done in this part of the document is guided by the inquiries concerning the differences between the clusters that are generated from the model in the CTC scenario and the one from the Present scenario. Figure 5.6 presents the current grouping, the generated by hierarchical clustering with Ward's linkage criterion and K-means algorithm. The analysis of these results is conducted one ACSS group at a time.

Considering solely the established category B, the results are globally consistent in both scenarios and methodologies. These providers present strong affinity with the units of group C. From all the hospitals that constitute this established class B, CHO is the one that would be more likely to being clustered in another group as it is placed in all the methods-scenarios tested in the class in which the most predominant ACSS group is C.

Regarding the subset C, it is visible that with time it becomes better defined. This is evidenced by comparing the constitution of the classes in which these hospitals are put in. In a more quantitative approach this is evidenced by the ratio between the hospitals identified as the original C class over the total of hospitals presented in the same novel(s) class(es). In CTC scenario the value is 0.833, which compares to the 0.933 of the Present scenario. Both these results are the arithmetic average of the pair of methods used.

As mentioned in Section 6.1.1, the providers of D class are the most disperse in the novel grouping (outputs from both the K-means and hierarchical) in the scenario CTC, presented in the Figure 5.4. CHUA is a hospital that in all the scenarios and algorithms is placed into either singles groups or in subsets in which it is the only representative of the established class. This suggests that CHUA should be placed in a different group. HPDFF also appears in the Present Scenario outside the corresponding peers of the ACSS category, this is reported in both methods. It is placed in clusters in which the other hospitals belonging to the current C group. This shows that HPDFF would be better grouped in a subset that contains the C elements and not the D.

The elements of category E exhibit the same pattern in the two temporal scenarios under analysis. All these units aggregate together in a unique class without any other provider, with the exception of CHLO. This unit is placed in the groups that contain the majority of the D class hospitals. Thus, the experimental results suggest that CHLO is not integrated in the most suitable category.

As expected, there was a significant proportion of hospitals aggregated in a very similar way between the scenarios. However, there are divergences in the results between the CTC and the Present scenario. Hospitals such as the CHUA, CHLO, HPDFF and CHO exhibit a pattern that points to changes in the currently grouping performed by ACSS years ago. CHUA and CHO are hospitals that suffered structural changes due to fusions of hospitals and hospital centers between the CTC and Present scenario. Therefore, it seems fair to affirm that merges or division of hospitals/hospital centers of the grouping should be revisited.

6.2.2 Financial impact

This section aims at replying to the question of the financial impact if the funding of the units contemplates the novel groupings proposed. The first row of Table 5.7 contains the values that are central to this debate.

There were constraints regarding the lack of access to the variables utilized in the original process and that were employed in definition of the values for the reimbursement of the medical consultations, the procedure is declared in the ACSS (2012). So an approximation model had to be conceived and implemented.

The value considered adequate to fund the hospital in our experimental model diverge from the current one. This divergence increases with time. In the year of 2013 these differences are estimated to be of 10.19% and it enlarges to 20.26% in 2017. Furthermore, in 2013 the new groups would produce savings, which is inverted in the 2017 scenario, indicating that the effect of the groups in the funding increment with time, which highlights the relevance of reviewing the groups.

The calculations are settled upon the assumption that the ratio of the unitary costs of medical consultations over the standard patient cost is invariant in time. Consequently, it is speculated that the gap between the estimated value that should be paid considering the novel grouping is over 100 million €. This amount should be additionally paid to the providers, solely for the year of 2017. This significant divergent, of 20% of the actual funding for the same activity, means there was an increment of the costs of the medical consultations over the total costs of standard patient. This affirmation only applies to the providers that presented the lowest cost per group. However, if the price practiced was adequate for the activity that is reimbursed, such a high difference (20%) would not be expected.

This strongly indicts that groups utilized for funding are not adequate, reinforcing the need for revisiting them. This position is in accordance with the idea that the root of the problem is located in considerations that were made in the definitions of the prices in 2013. As it is stated certain hospitals were identified to be in a frontier zone. Thus, it is possible that these could be placed in a class, in which the remaining units had higher unit costs. Consequently, the price that was identified is the lowest of the group, but if the unit does not fit properly the group, then it can artificially cause the dropping of the values.

Additionally, due to the metrics of access regarding medical appointments, it is visible that there is room for improvement. So, not only should attention be given to the unit price for consultations, but there should also be an increase in the production hired to the hospitals.

6.2.3 Characterization of the novel groups

Figure 5.3 and Figure 5.5 illustrate the features that better determine the distribution of the providers in the CTC scenario. While, Figure 5.7 and Figure 5.8, are their equivalents for the Present scenario in the same order. These images are experimental results that allow us to reply to the last question directed to the phase 2 of the work.

There are two major aspects to comment with respect to this enquire. Firstly, considering all the factors in the four studied cases the number of equivalent patients is the most important feature in defining and dividing the different groups proposed, as it is present in the three of the four cases.

Secondly, the factors that best describe the subsets diverge significantly between the temporal scenarios. Thus. substantial modifications occurred in the variables that explain the cost and the efficiency of a unit, since these are the dimensions covered by the models of Phase 2. Therefore, clusters should be reviewed and submitted to a new clustering process, even if the variables measured remained unchanged.

6.3 Phase 3: Impact of access, quality and environmental features

In this section the meaningful results produced in Phase 3 are discussed. This encompasses the generated outputs of the clustering algorithms applied to the data sets regarding access, quality, efficiency and environmental variables.

6.3.1 Comparison of the results of phase 2 and of phase 3

This part of the document tackles the first two questions raised in the listed objectives in Section 1.2. They are:

- Following the methodology of Phase 2 but including the access, quality and environmental factors in the data sets, which results do we obtain? Do they match the previous analysis ?
- When the same methodology is applied to the most recent data available do the results coincide with the model that uses the data contemporary to the model that established the currently accepted grouping? And what about the established groups?

Figure 5.9 and Figure 5.12 are the images from which the following discussion derives.

In the Present scenario CHO is the only unit of class B placed in a different subset out of all the providers in this category. This situation is identical to the reported in Phase 1, in which solely the original variables are considered (see Section 6.2.1). CHO is placed in a subset in which all the other providers are attributed with higher payments in respect to the same service (consultations). It is speculated that this unit is being underfunded. This claim is sustained by the fact that this provider had the lowest performance regarding access of the ACSS class, for the years that data is available (2018 and 2019), as depicted in Figure 5.15.

The pattern of group C contrasts with the above mentioned class. No indictments are found that support the idea that an element of this category is misplaced under the current classification. The major tendency to be noted is concerning the emergence of the division of this class into two subgroups. However,this trend is only observed in the models that include additionally access, quality and environment data.

The ACSS class D overall does not exhibit the pattern described in the case of the original features, discussed in Section 6.2.1. The exception to this statement is HPDFF. This provider expresses the same behaviour as in Phase 2. It has a lower affinity with the members in the Present scenario than in the CTC scenario. In Phase 2, HPDFF was the only provider of this group being clustered apart of their ACSS peers in the Present scenario. Although, in Phase 3 HGO also displays this pattern. This can be partially understood by the fact that this pair of providers have very similar patterns regarding the cost per equivalent patient and the performance on the access for medical appointments throughout time, illustrated in Figure 5.17, suggesting that these units share certain characteristics.

Finally, the currently E group shows very consistent results for both scenarios. In the CTC scenario, CHLO is placed in a group in which it is the only provider of his established class. This situation is observed not only for the scenario CTC but also for the Present one when the data sets used contained solely original variables, as described in Section 6.2.1. In Present scenario of Phase 3 this tendency is verified. This tendency is also present in the other hospital centers of the Lisbon region (CHULC and CHULN). They appear joined in a novel subset. Consequently, when a more holistic view of the providers is tested, class E is replaced by two sub-groups, according to the most recent data available.

These three hospital centers have the highest costs per equivalent patient of the group, as depicted in Figure 5.18. In addition, the majority of the population that these units serve belongs to the same municipality (Lisbon), which is reflected in the very similar characterization of the providers concerning the environmental variables. Despite the absence of the causality and correlation analysis between environmental aspects and the costs, efficiency and the activity of the healthcare units, the practical results indicts that the performance of the providers is influenced by the population served, according to the consulted literature .

In conclusion, the results point to the urgency for revision of the dimensions included in the clustering process. Even though, if the focus is to keep on grouping the hospitals solely by production and efficiency perspective, environmental factors ought to be taken into account for adequate assessment and grouping.

For both the scenarios covered by Phase 3 the method which produces the best division of the healthcare units is the hierarchical clustering with the euclidean distance and the Ward's linkage criterion.

6.3.2 Financial impact

Hereby the queries regarding the funding effect of the hospitals that would be generated if the novel proposed groups were considered are answered.

Applying the current funding schemes for the new categorization of providers would bring savings of around € 13 million for the CTC scenario and increment this expense over € 59 million for the Present scenario, as depicted in Table 5.7. Once again, the considered classes are obtained from the algorithm that scores the highest value in the silhouette criterion, which was achieved in both these cases by the hierarchical clustering algorithm with Ward's linkage criterion. This clustering technique also corresponds to the algorithm exhibiting the best performance regarding the internal criterion for the CTC scenario of phase 2. Therefore, it should be underlined that this common method was the one originally implemented by ACSS, as stated in ACSS (2012), validating the approach taken.

There are two other major aspects regarding this topic worth addressing. Firstly, it is worth again noticing that the time dimension by itself reveals the need for revision the scheme for paying the consultations, as the price that should be paid to the hospitals for their activity should significantly increase.

Secondly, it could be expected that the inclusion of access and quality aspects in the clustering process would lead to higher reimbursements value for the providers. But the incorporation of features covering the quality and access dimensions in the clustering process only means that the similarly distances measured between data instances include how close are the hospitals regarding these two domains in comparison with others. There is no qualitative evaluation whether these values are good or bad. So, it should not be expected that introducing of novel features would produce higher payments, since the considered variables present mix scales concerning the relation between the value and the performance of the unit on that particular aspect. For example, the higher the values are in the access values, the better is a hospital doing in respect to that dimension. On the contrary, the higher the values on the quality features, the worse the performance of the unit.

6.3.3 Characterization of the novel groups

As for the section with the same denomination for Phase 2, the features that define the separation of the providers by the subsets generated are tackled here. The images displaying this information are Figure 5.10 and Figure 5.11 regarding the CTC scenario. The respective equivalents for Present scenario are Figure 5.13 and Figure 5.14.

There is a couple of relevant ideas to be expressed regarding the topic of the characterization of the proposed groups. First, the aggregation of healthcare units in Phase 3, in which the model includes the original factors and quality, access and environmental information as well, show that the constitution of the subsets vary between the two temporal scenarios, as in Phase 2. These changes are thought to be caused by the transformation that occurred in the hospitals between the scenarios covered.

Second, for the most recent scenario the hospitals covered in this study are better clustered by the models in Phase 3, which encompass all the same features of Phase 2 and features which assess the access, quality and environmental dimensions. This statement is supported by the values that Silhouette index assumes regarding the tested methods in Phase 2 and Phase 3, depicted in Tables 5.4 and 5.6, respectively. The silhouette values concerning the aggregation achieved on Phase 3 are higher than those met in Phase 2. Therefore, the data sets that incorporate all the dimensions mentioned above are placed into subsets of more homogeneous healthcare providers, thus it is recommend to incorporate the feature covering access, quality and environmental factors in the clustering of hospitals.

6.4 Managerial and Political impacts

This section outlines the main repercussions that the results of this work elicit concerning the political and administration frames for the healthcare providers covered.

6.4.1 Importance of these results for the stakeholders

The next paragraphs are dedicated to succinctly highlight the relevance of the experimental results for the stakeholders: policy makers, hospital managers, staff (clinical and non-clinical) and the citizens.

First, this work alerts the policy makers to the urgent necessity of reviewing the hospital groups, as these do not adequately translate the current reality of the healthcare providers. Considering that the established grouping of hospitals is on the basis of the benchmarking process and is involved in the definition of the funding for these units, this inadequacy discredits the trust on these fundamental activities, as they are being conducted in accordance to the highest level of fairness.

It is estimated that this inadequacy is causing an overall underfunding of the general public hospitals EPE ranging between € 59-110 millions/year. This situation can be a relevant factor to explain the significantly less than ideal performance of the HS regarding the access of its citizens to healthcare services, since the costs constrains can effect negatively quality and access of the healthcare services (Ferreira et al., 2020). The literature reports the negative impacts of the austerity measures and policies enforced in the NHS between 2011 and 2015 had on the access of the citizens to healthcare services. In post-crisis period policies were implemented to address this issue (Nunes and Ferreira, 2019). Although, access remains a severe problem for the Portuguese NHS, as depicted by the recent report of Mendes et al. (2019). This reality can be also noted by the graphics showing the proportion of medical appointments made by the studied units under the adequate period, see Figure 5.15, Figure 5.16, Figure 5.17 and Figure 5.18.

The hypothesis that this underfunding can be possibly contributing to this matter is reinforced. Consequently the correction of the hospital grouping should be a priority for the responsible institutions. Additionally this rectification presents a opportunity for the MH and ACSS to the enact adjustments in the incentives and penalties contemplated in the reimbursement schemes. The application of these components should be adapted to each of the (novel) subsets of providers, contrasting with the generalist character of their application in the contract-programs.

A fast action towards the revision and correction of the funding amounts for the healthcare of the units can signal its confidence in the managerial teams of the healthcare units. Even more in a context in which the attribution of more responsibilities and control in the governance for the administrations of the hospitals is demanded.

Second, the relevance for hospital managers is strongly related to the elements put up for describing the pertinence of this dissertation for the political players. through the perspective of the hospitals. This works gives strong arguments for the revision and increment of the funding for the healthcare units, that would result from the revision of the underlying categorization of hospitals. Additionally, it gives arguments that at least partly justify the negative aspects referred above. Consequently, it should reinforce the position of the administrations boards regarding the request for higher autonomy of management of the units that are under their supervision and responsibility.

In addition, the updating of the grouping that is implemented in the benchmarking process is pertinent for these stakeholders. Because, not only does it impact the funding of these units, through the benchmarking incentive, but also implies that the evaluation can be misidentifying the best/worst providers, according the multiple perspectives evaluated.

The staff can be impacted by the weakness of perceptions that the allocation of the resources to the different units and also the assessment of the performance of the institution they work for. This can affect the motivation of the workers, since it can undermine the perception of fairness of the distribution of resources between the units, and consequently impact the recognition of the achievement of their product in benchmarking tables.

Finally, this work is relevant for the citizen as the end user and also the indirect financier of the HS (tax funded), as this work reflects and tackles a mechanism that supports the evaluation and funding part of the HS. It is very relevant that the application of the money is faired and perceived as fair.

6.4.2 Principal implications in the management and funding

Hereby are presented the major impacts of this work for the funding and administration of the hospital units covered by this study.

First, a revision should be made to the grouping of the public hospitals to ensure that both the funding and benchmarking of these providers are conducted based upon a model that reflects the current reality of the institutions. This process also offers the advantage to improve the fairness of the categorization of healthcare providers, as more data is gathered and available than at the moment of the generation of the creation of the established division. Ergo, a broader and more complete vision of the units can be achieved.

Second, the dimension that the incorporated variables cover in the clustering process also should be reconsidered. Efficiency is a very relevant topic that should keep being included in the process, as financial sustainability is fundamental for any HS, as long as the pursue of efficiency does not undermine the quality and access of the healthcare services that are defined as acceptable. So, features of the three key-factors should be included in the aggregation procedure: efficiency, quality and access. Moreover, environmental factors should also be enclosed in the process due to their impact not only on the costs of the activity impact, but also social and economical factors that influence the activity of the healthcare services, and vice-versa. Furthermore, this decision is supported by the fact that the study concludes that for the present scenario the general public hospitals EPE are better aggregated when all these dimensions are encompassed.

The application of the hospital groups for the important tasks that are currently utilized, benchmarking and funding, should also be reevaluated. The results produced in this work point to the strong distinctiveness of the healthcare units studied. Therefore, considering the grouping for these tasks should be done with caution. Specially because the determination of the price for an activity as critical for the hospitals as the external medical appointments are based on it. The assumptions is that the units belonging to the placed group are so similar that the one that has the lowest cost in providing this service is the most efficient. This is not the most adequate approach for two aspects. One, there can be exogenous factors to the hospital that influence the lower costs: factors of income, more healthy habits, use of healthcare services in private providers. Two, the quality of the service was not considered in the determination of the price, neither was the access.

Lastly, there were generated decision trees (i.e Figure 5.13) which are interpretable diagrams that unveil the criteria of the aggregation of the units by translating the mathematical-based process. This provides important information that can support the process of decisions for political and/or management decisions regarding the general public hospitals.

Chapter 7

Conclusions

The current grouping of the Portuguese hospitals of NHS should be reviewed given that it diverges from the categorization that best describes the units covered. It is estimated that this inadequacy is causing an overall underfunding of the general public hospitals EPE ranging between €59-110 millions/year.

The reexamination is necessary for three reasons. First, the developed model strongly indicts that the established categorization does not adequately translate the reality of the providers, due to the transformations that occurred in the hospital organizations after its publication in 2011. Second, the current hospital categorization does not contemplate crucial aspects such as the quality and access associated to the provision of healthcare services. Third, the original procedure fails to include the environmental features that characterise the populations served by these providers, when this dimension deeply impacts the clinical activity and the care provision.

Therefore a new clustering analysis should be performed considering the most recent data and incorporating access, efficiency, quality and environmental dimensions.

7.1 Achievements

The major achievements of the present work are:

- Development of a model which replicates the clustering process that generated the established hospital groups for the general public hospitals;
- Analysis of the evolution of the grouping that should be observed in case the most recent available information is considered;
- Study of the influence of the inclusion of access, quality and environmental factors on the subsets that result from the clustering of the general public hospitals.
- Generation of decision trees that facilitate the visualization of the variables that define the division of the healthcare providers studied regarding the novel groups;
- Estimation of the financial impact that would result from the implementation of the produced hospital groups under the contemporary payment schemes.

7.2 Limitations and Future Work

The main challenges and difficulties experienced through this work are the time scenarios and the variables covered. The identified future work directions aim at overcoming the identified limitations. First, a higher range of temporal scenarios should be analysed. For instance, all the years between the formation of the hospital classes and the present year could be included in the study. This would permit to identify more precisely when the changes in the grouping occurred and consequently to comprehend the transformation in the healthcare providers that led to this outcome.

Regarding the variables, three major aspects can be addressed. One, the model should incorporate quality, access and environmental dimensions in addition to the currently enclosed factors concerning the capacity and activity of the healthcare services. Two, categorical ordinal variables such as the types of urgency were handled as non-ordinal, resulting in information loss. To overcome this, numeric encoding can be used to specify the distances between the different categories. Three, efforts can be made to ensure that all information gathered by the MH and ACSS is made available for the study, to ensure that the results and inherently the derived conclusions are more reliable and useful for the polices and management decision makers.

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Appendix A

Other experimental results

Table A.1: Results of the analysis for the strongest predictors of numerical features for all tested clustering combinations to the data with the original variables, with the number of clusters = 4. This analysis was made with the dataset without being applied PCA

ID	Best numerical predictor			2nd Best numerical predictor		
	Feature	F-measure	P-value	Feature	F-measure	P-value
1	CDTT Total	4.129204e+01	1.240958e-09	Internal CDTT	41.165887	1.279423e-09
2	ICM surgical ambulatory	3.839147e+01	2.555139e-09	Nurses	35.128666	6.086177e-09
3	Nurses	6.243762e+01	1.756394e-11	Urgency Type - SUMC	56.285714	5.229446e-11
4	Nurses	1.038498e+02	6.980361e-14	Internal CDTT	54.573245	7.217592e-11
5	Nurses	7.579307e+01	2.206977e-12	ICM surgical hospitalization	45.569995	4.603156e-10
6	Nurses	4.072705e+01	1.423618e-09	Internal CDTT	32.167176	1.418227e-08
7	Urgency Type - SUP	5.295238e+01	9.871745e-11	Urgency Type - SUMC	52.00	1.191218e-10
8	Nurses	6.119947e+01	2.170647e-11	CDTT Total	40.753699	1.414376e-09
9	Urgency Type - Urgency Type - SUP	6.305039e+16	7.015813e-191	CDTT Total	39.932988	1.731317e-09
10	Nurses	4.869116e+01	2.343336e-10	ICM surgical ambulatory	33.404106	9.888670e-09
11	Urgency Type - SUP	inf	0.000000e+00	Nurses	66.676654	8.739751e-12
12	CDTT Total	6.402432e+01	1.346131e-11	Internal CDTT	63.411941	1.490646e-11
13	University hospital	3.610000e+01	4.669393e-09	ICM medical ambulatory	29.806221	2.913152e-08
14	Nurses	2.626142e+01	9.374093e-08	Internal CDTT	24.814995	1.563425e-07
15	Nurses	4.614786e+01	4.050508e-10	CDTT Total	30.653068	2.239069e-08
16	Nurses	4.254188e+01	9.208883e-10	Operating rooms	42.265085	9.831543e-10

The figure A.1 illustrates in a heat map the distance between all the healthcare units that are analysed, according to the 4 different metrics used. Distance matrix for all the hospitals in the sample.

Table A.2: Results of the analysis for the strongest predictors of categorical features for all tested clustering combinations to the data with the original variables, with the number of clusters = 4. This analysis was made with the dataset without being applied PCA

ID	**Best categorical predictor**			**2nd Best categorical predictor**		
	Feature	χ^2	P-value	Feature	χ^2	P-value
1	University hospital	14.466667	0.002334	Urgency Type - SUP	12.111111	0.007012
2	University hospital	14.050000	0.002838	Urgency Type - SUP	11.945833	0.007571
3	University hospital	10.885714	0.012360	Urgency Type - SUP	10.133333	0.017466
4	University hospital	12.866667	0.004934	Urgency Type - SUP	10.106838	0.017679
5	University hospital	12.422222	0.006068	Urgency Type - SUP	10.166667	0.017201
6	University hospital	21.000000	0.000105	Urgency Type - SUP	4.644444	0.199762
7	Urgency Type - SUP	13.900000	0.003044	University hospital	10.542857	0.014473
8	University hospital	11.250000	0.010448	Urgency Type - SUP	8.562500	0.035710
9	Urgency Type - SUP	16.000000	0.001134	University hospital	14.371429	0.002441
10	University hospital	21.000000	0.000105	Urgency Type - SUP	7.076023	0.069514
11	Urgency Type - SUP	16.000000	0.001134	University hospital	11.571429	0.009005
12	University hospital	10.952381	0.011986	Urgency Type - SUP	9.333333	0.025172
13	University hospital	17.190476	0.000646	Urgency Type - SUP	6.000000	0.111610
14	University hospital	21.000000	0.000105	Urgency Type - SUP	6.000000	0.111610
15	University hospital	13.727273	0.003301	Urgency Type - SUP	4.863636	0.182059
16	University hospital	10.565217	0.014325	Urgency Type - SUP	3.826087	0.280866

Table A.3: Results of the analysis for the strongest predictors of numerical features for all tested clustering combinations to the data with the original variables, with the number of clusters = 5. This analysis was made with the dataset without being applied PCA

ID	Best numerical predictor			2nd Best numerical predictor		
	Feature	F-measure	P-value	Feature	F-measure	P-value
1	ICM internamento cirúrgico	40.304490	4.492339e-10	Urgency Type - SUP	36.964286	1.057011e-09
2	Urgency Type - SUP	43.535714	2.077244e-10	ICM surgical ambulatory	29.062751	1.075270e-08
3	Nurses	61.549904	5.961709e-12	CDTT Total	58.033346	1.099906e-11
4	Nurses	138.059534	1.005206e-15	Operating rooms	58.225665	1.062765e-11
5	Nurses	59.850947	7.981969e-12	ICM surgical hospitalization	40.686836	4.089252e-10
6	Nurses	37.867982	8.332716e-10	Internal CDTT	26.709857	2.373258e-08
7	Urgency Type - SUMC	43.535714	2.077244e-10	Nurses	40.282489	4.516812e-10
8	Nurses	46.946806	9.696774e-11	ICM surgical hospitalization	33.355188	2.879203e-09
9	Urgency Type - SUP	inf	0.000000e+00	Urgency Type - SUMC	38.607143	6.884261e-10
10	Nurses	37.867982	8.332716e-10	Internal CDTT	26.709857	2.373258e-08
11	Urgency Type - SUP	inf	0.000000e+00	Nurses	50.743882	4.389099e-11
12	Nurses	52.457216	3.122316e-11	CDTT Total	46.702796	1.022308e-10
13	Nurses	39.215158	5.897356e-10	Internal CDTT	28.628246	1.239542e-08
14	Nurses	36.297052	1.263969e-09	CDTT Total	25.594291	3.523619e-08
15	Nurses	39.215158	5.897356e-10	Internal CDTT	28.628246	1.239542e-08
16	Operating rooms	36.250501	1.279970e-09	Nurses	35.030799	1.788584e-09

Table A.4: Results of the analysis for the strongest predictors of categorical features for all tested clustering combinations to the data with the original variables, with the number of clusters = 5. This analysis was made with the dataset without being applied PCA

ID	**Best categorical predictor**			**2nd Best categorical predictor**		
	Feature	χ^2	P-value	Feature	χ^2	P-value
1	University hospital	15.333333	0.004058	Urgency Type - SUP	13.846154	0.007803
2	University hospital	17.266667	0.001715	Urgency Type - SUP	14.133333	0.006881
3	Urgency Type - SUP	13.900000	0.007621	University hospital	11.904762	0.018074
4	University hospital	12.866667	0.011946	Urgency Type - SUP	10.106838	0.038666
5	University hospital	14.222222	0.006619	Urgency Type - SUP	10.166667	0.037712
6	University hospital	21.000000	0.000317	Urgency Type - SUP	7.185185	0.126420
7	Urgency Type - SUP	13.900000	0.007621	University hospital	11.304762	0.023344
8	University hospital	11.266667	0.023725	Urgency Type - SUP	8.650000	0.070469
9	University hospital	17.800000	0.001350	Urgency Type - SUP	16.000000	0.003019
10	University hospital	21.000000	0.000317	Urgency Type - SUP	7.185185	0.126420
11	Urgency Type - SUP	16.000000	0.003019	University hospital	11.704762	0.019687
12	University hospital	11.666667	0.020010	Urgency Type - SUP	9.350000	0.052922
13	University hospital	17.190476	0.001775	Urgency Type - SUP	6.000000	0.199148
14	University hospital	21.000000	0.000317	Urgency Type - SUP	6.000000	0.199148
15	University hospital	17.190476	0.001775	Urgency Type - SUP	6.000000	0.199148
16	University hospital	13.727273	0.008218	Urgency Type - SUP	4.863636	0.301578

Table A.5: Results of the analysis for the strongest predictors of numerical features for DBSCAN clustering. This analysis was made with the dataset without being applied PCA

ID	Best numerical predictor			2nd Best numerical predictor		
	Feature	F-measure	P-value	Feature	F-measure	P-value
17	Beds in specialized units	89.852865	5.452866e-08	Nurses	78.336716	1.001795e-07
18	Beds in specialized units	89.852865	5.452866e-08	Nurses	78.336716	1.001795e-07
19	Beds in specialized units	89.852865	5.452866e-08	Nurses	78.336716	1.001795e-07
20	Beds in specialized units	89.852865	5.452866e-08	Nurses	78.336716	1.001795e-07

Table A.6: Results of the analysis for the strongest predictors of categorical features for DBSCAN clustering. This analysis was made with the dataset without being applied PCA

ID	Best categorical predictor			2nd Best categorical predictor		
	Feature	χ^2	P-value	Feature	χ^2	P-value
		Adjusted Rand index	Silhouette	Numerical	Categorical	
17	University hospital	21.0	0.279413	Urgency Type - SUP	16.0	0.592547
18	University hospital	21.0	0.279413	Urgency Type - SUP	16.0	0.592547
19	University hospital	21.0	0.279413	Urgency Type - SUP	16.0	0.592547
20	University hospital	21.0	0.279413	Urgency Type - SUP	16.0	0.592547

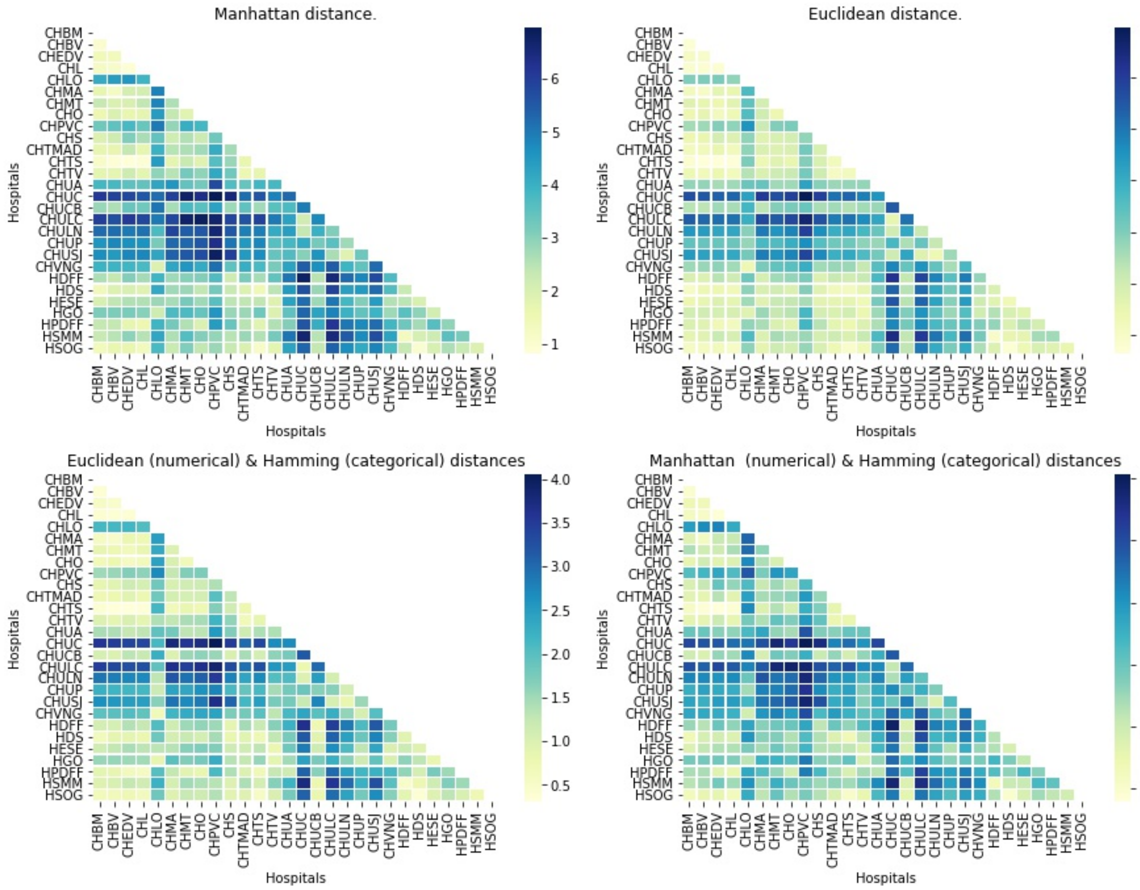

Figure A.1: Heatmap depicting the distances between hospitals regarding the four metrics tested, in the CTC scenario for phase 1

Table A.7: Data set for the CTC scenario according to original features. Part 1 out of 2

Hospital	ICM medical hospitalization	ICM surgical hospitalization	ICM surgical ambulatory	ICM medical ambulatory	ORs	Beds in Spu	Nurses	Medical hours	Hospitalization episodes	Internal CDTT
textbfCHBM	0.7711	0.9900	0.3592	0.2242	6	5	554	81895.700000	12346	2295357.0
CHBV	0.8480	0.8745	0.3614	0.2110	7	6	673	75617.000000	18235	1640108.0
CHEDV	0.8200	0.9262	0.3100	0.2293	10	10	447	123343.530000	19724	2713566.0
CHL	0.8420	0.8850	0.3684	0.2344	19	10	390	101143.850000	22497	1964206.0
CHLO	1.0060	2.0706	0.6839	0.2323	23	33	1162	68669.010000	26445	4017528.0
CHMA	0.7148	0.6097	0.3524	0.2135	7	0	362	50939.473667	12425	1555525.0
CHMT	0.9297	0.9460	0.3199	0.2312	6	0	707	189672.900000	16913	3881492.0
CHO	0.7693	0.7661	0.3192	0.2351	6	0	576	199370.533333	16645	2158074.0
CHPVC	0.6069	0.5502	0.3332	0.3287	2	0	212	50613.160000	7349	786493.0
CHS	0.8231	1.2412	0.4874	0.2016	8	6	695	120057.500000	1425	1994197.0
CHTMAD	0.8941	0.9912	0.3247	0.2134	11	8	854	80069.750000	23327	3981596.0
CHTS	0.8313	0.8104	0.3233	0.2131	9	6	528	77449.000000	20303	2744903.0
CHTV	0.8730	1.1586	0.3525	0.2255	14	8	802	49428.100000	22745	2627462.0
CHUA	0.8626	1.2989	0.3972	0.2326	12	42	1384	185394.480000	14100	3106885.0
CHUC	1.0146	1.7293	0.4594	0.2184	52	46	2800	28068.230000	65962	10279058.0
CHUCB	0.8992	0.8275	0.3481	0.1992	6	6	409	29138.023333	12528	1828676.0
CHULC	1.0410	2.0469	0.4293	0.2198	58	94	2589	14842.760000	50113	8773946.5
CHULN	1.1370	1.7992	0.5479	0.2169	29	29	2008	53072.306700	46823	7828728.0
CHUP	0.9819	1.5089	0.4678	0.2085	21	26	1125	43509.050000	31521	5133467.0
CHUSJ	1.0855	1.9723	0.4654	0.2319	32	55	2104	22128.058889	41915	7268835.0
CHVNG	0.8654	1.4998	0.7070	0.2270	16	12	938	23173.890000	22825	3708579.0
HDFF	1.0846	0.8685	0.4318	0.1981	2	0	197	19420.000000	6393	936301.0
HDS	0.8481	0.9238	0.3499	0.2243	7	6	481	71629.113953	15851	4341270.0
HESE	0.8464	0.9607	0.4078	0.2353	6	5	486	58116.550000	11785	2665151.0
HGO	0.9795	1.8197	0.4139	0.2204	11	12	889	116755.933333	21033	2888044.0
HPDFF	0.9846	0.9143	0.3448	0.2241	21	26	793	153640.215333	32224	3032669.0
HSMM	0.9882	0.6040	0.3203	0.2247	2	0	177	34427.000000	5192	555162.0
HSOG	0.8516	0.9313	0.3086	0.2313	13	6	613	46180.674416	20405	2751161.0

MH - medical hospitalization; SH - surgical hospitalization; SA - surgical ambulatory; MA - medical ambulatory; ORs - Operation rooms; Spu - specialized units; HE - Hospitalization episodes; US - Urgency services; Int - Internal; RR - Ratio of Resident physicians; UE - Urgency Episodes; EP - Equivalent Patients Univ - University hospital

Table A.8: Data set for the CTC scenario according to original features. Part 2 out of 2

Hospital	Beds	Medical appointments	Ratio of Resident physicians	Urgency episodes	Equivalent patients	Total CDTT	UT - SUP	UT - SUMC	UT - SUB	University hospital
CHBM	353	38517	0.387416	149256	1416079.78	2300802	0	1	1	0
CHBV	426	66651	0.342734	176896	2028557.17	1642245	0	1	1	0
CHEDV	356	116832	0.375603	178773	2286788.20	2739274	0	1	1	0
CHL	503	69791	0.386653	169957	2416729.49	2020347	0	1	1	0
CHLO	797	101956	0.411474	148322	2885239.04	4018262	1	0	0	0
CHMA	281	46481	0.299885	124319	1426729.10	1578750	0	1	1	0
CHMT	427	64691	0.297760	149832	1859156.13	3910800	0	1	1	0
CHO	201	46448	0.393875	202887	1890114.02	2235295	0	1	1	0
CHPVC	143	2644	0.249183	78469	805719.90	841250	0	1	0	0
CHS	380	6322	0.336587	128445	349284.79	2010686	0	1	0	0
CHTMAD	603	8031	0.379310	168892	2465555.32	4024872	1	1	1	0
CHTS	435	92424	0.382672	175180	2327413.22	2781632	0	1	1	0
CHTV	650	72872	0.375328	169301	2551373.75	2627925	1	0	1	0
CHUA	906	90454	0.374886	212720	1773020.05	3125431	1	1	1	1
CHUC	1933	205978	0.419688	287530	6977286.02	10319955	1	0	0	1
CHUCB	317	48766	0.344096	77831	1343185.08	1828727	0	1	0	1
CHULC	1462	204055	0.373433	236552	5451648.51	8798908	1	0	0	1
CHULN	1168	184839	0.437026	198524	4982217.47	7916463	1	0	0	1
CHUP	707	156333	0.378075	2482	3421804.39	5146346	1	0	0	1
CHUSJ	1106	168617	0.403900	289172	4639437.00	7277861	1	0	1	1
CHVNG	550	130731	0.404801	68150	2498408.20	3762695	1	0	0	0
HDFF	144	25275	0.363136	71674	724520.38	944732	0	1	0	0
HDS	373	38992	0.422873	123388	1726471.15	4355491	0	1	0	0
HESE	331	56734	0.369540	69680	1312809.69	2760610	1	0	0	0
HGO	545	83848	0.396395	146445	2305596.86	2896861	1	0	0	0
HPDFF	772	88469	0.420147	197215	3410233.79	3056205	0	1	1	0
HSMM	124	19407	0.400839	73120	604222.24	574059	0	1	0	0
HSOG	455	73539	0.396305	143494	2230831.66	2753128	0	1	0	0

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Table A.9: Data set for the Present scenario according to original features. Part 1 out of 2

Hospital	Internal CDTT	ICM hospitalization	ICM surgical ambulatory	ICM medical ambulatory	ORs	Beds in Spu	Medical hours	Beds	Nurses	Hospitalization episodes
CHBM	1.933056e+06	0.8030	0.6525	0.2097	6	5	81895.700000	4677	7874	69443
CHBV	1.381232e+06	0.8033	0.6444	0.2044	7	6	75617.000000	4897	8770	103441
CHEDV	2.285255e+06	0.8268	0.6443	0.2082	10	10	123343.530000	4392	8044	111623
CHL	1.654174e+06	0.7586	0.6404	0.2151	19	10	101143.850000	6036	9991	121151
CHLO	3.383398e+06	1.1513	0.7089	0.2283	23	33	68669.010000	9499	16761	149968
CHMA	1.310000e+06	0.6260	0.6119	0.2072	7	0	50939.473667	2964	4674	58253
CHMT	3.268834e+06	0.7551	0.6257	0.2073	6	0	189672.900000	4946	9096	100229
CHO	1.817442e+06	0.7909	0.6666	0.2159	6	0	199370.533333	3913	7187	89456
CHPVC	6.623524e+05	0.6757	0.6943	0.2063	2	0	50613.160000	1716	3144	49584
CHS	1.679431e+06	0.8847	0.6758	0.2009	8	6	120057.500000	4542	9201	90323
CHTMAD	3.353138e+06	0.8648	0.6329	0.2054	11	8	80069.750000	6734	12141	160733
CHTS	2.311645e+06	0.7970	0.6646	0.1864	9	6	77449.000000	5069	8086	134637
CHTV	2.212741e+06	0.8891	0.6611	0.2202	14	8	49428.100000	7524	11065	126127
CHUA	2.616492e+06	0.8152	0.6725	0.2137	12	42	185394.480000	11169	19075	182169
CHUC	8.656604e+06	1.0911	0.6418	0.2074	52	46	28068.230000	20532	35074	369272
CHUCB	1.540036e+06	0.7874	0.6911	0.1982	6	6	29138.023333	3643	4776	60228
CHULC	7.389060e+06	1.2976	0.6545	0.2112	58	94	14842.760000	14136	31361	271358
CHULN	6.593036e+06	1.3765	0.7051	0.2018	29	29	53072.306700	12691	23601	231904
CHUP	4.323197e+06	1.1195	0.6469	0.2027	21	26	43509.050000	8996	17553	198658
CHUSJ	6.121517e+06	1.3305	0.6346	0.2122	32	55	22128.058889	11971	28082	259448
CHVNG	3.123214e+06	1.0963	0.6974	0.2275	16	12	23173.890000	6936	14891	136621
HDFF	7.885145e+05	0.7975	0.6153	0.1972	2	0	19420.000000	1848	2597	33128
HDS	3.656041e+06	0.7585	0.6859	0.2047	7	6	71629.113953	5074	7173	94107
HESE	2.244482e+06	0.8411	0.6578	0.2222	6	5	58116.550000	3453	6628	73983
HGO	2.432193e+06	1.0346	0.6751	0.2150	11	12	116755.933333	7223	11665	122415
HPDFF	2.553990e+06	0.9611	0.6229	0.2008	21	26	153640.215333	9482	12259	157785
HSMM	4.675348e+05	0.7891	0.6149	0.2096	2	0	34427.000000	1404	2315	36554
HSOG	2.316916e+06	0.7836	0.6565	0.2106	13	6	46180.674416	6441	8112	134210

ORs - Operation rooms; Spu - specialized units

Table A.10: Data set for the Present scenario according to original features. Part 2 out of 2

Hospital	Medical appointments	Ratio of Resident physicians	Urgency episodes	Equivalent patients	Total CDTT	UT - SUP	UT - SUMC	UT - SUB	University hospital	Class 1 *	Class 2 *	Class 3 *
CHBM	183412	0.359652	1020703	7851802.67	1.937642e+06	0	1	1	0	1	0	0
CHBV	234613	0.336253	1129368	11474595.29	1.383032e+06	0	1	1	0	1	0	0
CHEDV	287253	0.367437	1393671	12600276.79	2.306905e+06	0	1	1	0	1	0	0
CHL	277963	0.370169	1210905	13202823.66	1.701454e+06	0	1	1	0	1	0	0
CHLO	463438	0.420825	1051236	16087926.16	3.384017e+06	1	0	0	0	0	0	1
CHMA	166378	0.253025	865199	6711780.73	1.329559e+06	0	1	1	0	1	0	0
CHMT	184737	0.324048	963239	10752336.91	3.293516e+06	0	1	1	0	1	0	0
CHO	145110	0.413271	1168669	9932609.68	1.882474e+06	0	1	1	0	1	0	0
CHPVC	92349	0.275723	474289	5344568.68	7.084665e+05	0	1	0	0	1	0	0
CHS	249370	0.375531	949364	9838633.80	1.693318e+06	0	1	0	0	1	0	0
CHTMAD	319914	0.364807	1189146	16802768.62	3.389583e+06	1	1	1	0	0	1	0
CHTS	320440	0.354017	1256242	14678076.99	2.342577e+06	0	1	1	0	1	0	0
CHTV	262262	0.377202	1037185	13543603.81	2.213131e+06	1	0	1	0	0	1	0
CHUA	300387	0.408529	2336923	20298677.72	2.632111e+06	1	1	1	1	0	1	0
CHUC	891836	0.395273	1938611	38583185.88	8.691046e+06	1	0	0	1	0	0	1
CHUCB	143060	0.429289	461993	6272106.28	1.540079e+06	0	1	0	1	1	0	0
CHULC	723040	0.374322	1589057	28608650.62	7.410082e+06	1	0	0	1	0	0	1
CHULN	738302	0.433924	1618615	24598031.44	6.666923e+06	1	0	0	1	0	0	1
CHUP	695273	0.391812	985443	20985854.54	4.334043e+06	1	0	0	1	0	0	1
CHUSJ	762827	0.390222	1667247	27562604.88	6.129118e+06	1	0	1	1	0	0	1
CHVNG	510811	0.373565	1195701	14988218.31	3.168788e+06	1	0	0	0	0	1	0
HDFF	91820	0.398880	476900	3735906.52	7.956148e+05	0	1	0	0	1	0	0
HDS	141392	0.385604	861609	10117702.67	3.668017e+06	0	1	0	0	1	0	0
HESE	195644	0.378508	485197	7938095.15	2.324873e+06	1	0	0	0	0	1	0
HGO	296956	0.347915	1073319	13244476.55	2.439618e+06	1	0	0	0	0	1	0
HPDFF	326147	0.410931	1686138	17001797.90	2.573811e+06	0	1	1	0	1	0	0
HSMM	80813	0.432392	411558	3972461.72	4.834491e+05	0	1	0	0	1	0	0
HSOG	264654	0.399208	906729	14134553.70	2.318572e+06	0	1	0	0	1	0	0

* - hospital classification according to *Carta Hospitalar* Decree no. 82/2014
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