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Prescribing patterns of medication for respiratory diseases: cluster analysis of the Portuguese electronic prescription database

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Key words

Asthma; chronic obstructive pulmonary disease; cluster analysis; electronic prescribing; retrospective studies.

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Summary

We aimed to describe, for the first time, the prescribing patterns among patients on persistent respiratory treatment, from the Portuguese electronic prescription and dispensing database. This was a one-year retrospective population-based analysis of prescriptions (n = 39810) for medication for respiratory diseases and exacerbations. Cluster analysis was applied based on medication and prescribers' specialty. Prescribing patterns were grouped and labelled as: possible medication for asthma and allergic rhinitis (General Practitioners-GPs and allergists to younger patients); COPD (GPs and pulmonologists to older patients); asthma or Asthma-COPD Overlap (GPs and pulmonologists); exacerbation, infection and relievers. This analysis was an important first step to understand the Portuguese reality on the treatment of respiratory diseases.

Impact statement

Eleven different prescription patterns were revealed by unsupervised analysis of prescriptions for respiratory diseases and exacerbations - from the Portuguese electronic prescription and dispensing database - providing a new understanding of the Portuguese reality on the treatment of respiratory diseases.

Introduction

The goals of asthma and chronic obstructive pulmonary disease (COPD) management are to reduce symptoms and minimize the risk of future exacerbations, obtained by continuous assessment, treatment, and review of the patient's response (1, 2). Asthma and COPD are heterogeneous diseases with similarities in symptoms and management options, moreover, some patients present an overlap of asthma and COPD features (asthma-COPD overlap - ACO). Although the use of the term ACO is controversial and both its concept and terminology are not robust, it is useful in clinical practice when patients cannot be clearly classified into asthma or COPD (1).

Real-world data (RWD) routinely collected in the course of healthcare delivery (3) have an important role in acknowledging the use and effects of treatments, and the overall heterogeneity of chronic diseases (4). RWD has also been used to describe medication prescribing for asthma and DPOC (5–7).

For the analysis of RWD, the unsupervised statistical techniques are increasingly popular approaches to identify and reveal new insights among healthcare data (8). They aim to reveal possible natural clusters grouped by similar characteristics, otherwise not be apparent, in other words, not defined *a priori*. Each cluster should be as homogenous as possible and have minimal overlapping to the other

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clusters. Common clustering methods are hierarchical, partitional and two-step (distance-based methods) and latent class analysis (model-based methods) (9). Unsupervised clustering methods have been used to reveal phenotypes of asthma (10, 11), COPD (12) and allergic diseases (13, 14), and to identify factors of increased healthcare utilization (15) and prescription patterns (16).

In Portugal the research based on RWD, namely based on the national electronic prescription database is scarce. Recently we reported an analysis of data from the Portuguese electronic prescription and dispensing database that showed an association between insufficient prescription of maintenance medication and over-prescription of short-acting beta2 agonists (SABA) and oral corticosteroids (OCS) (17). Further research on maintenance prescription patterns may contribute to a better understanding of the underlying challenges of the management of chronic respiratory diseases in "real-world" healthcare.

Aims

We aim to describe medication patterns in the Portuguese electronic prescription and dispensing database (Portuguese electronic prescription and dispensing database (*Base de Dados Nacional de Prescrições*) - BDNP), among patients over 15 years old with persistent respiratory treatment (PRT).

Methods

Study design

This study was a retrospective population-based analysis of a random sample of patients from the Portuguese electronic prescription and dispensing database (BDNP).

Setting/Data source

The BDNP records data of all the prescriptions and respective dispensing in mainland Portugal. The population of interest in this study consists of patients to whom medication for respiratory and/or allergic diseases and exacerbations was prescribed at least once, between January 2016 and December 2016. We obtained all the prescriptions from a random sample of 2% (n = 103647) of these patients, corresponding to 1129512 prescriptions (**figure 1**). A more detailed description of the data source has been previously published (17).

Participants

In this study, we analysed the prescriptions (n = 248045) between January 2016 and December 2016 for medications for respiratory and/or allergic diseases and exacerbations (**table I**), from a sample of patients from mainland Portugal, aged 15 years and above (**figure 1**). We analysed the prescriptions delivered to patients on persistent respiratory treatment (n = 8798, **figure 1**) and we considered different prescriptions ordered by the same prescriber, for the same patient, on the same day, as a unique prescription (n = 39810, **figure 1**).

Variables

Persistent respiratory treatment (PRT) was defined as having prescriptions for more than 2 packages of any of the six classes of respiratory maintenance medications: inhaled corticosteroids (ICS) alone or in fixed-dose combination with long-acting beta2 agonists (LABA); leukotriene receptors antagonists (LTRA); long-acting muscarinic antagonist (LAMA) alone or in a fixed-dose combination with LABA or LABA alone.

Table I *- Frequency of prescribed packages of medication for respiratory diseases and exacerbations.*

Medication classes	**Packages n = 312527**	
	n	**%**
Maintenance		
ICS + LABA	37 007	11.8
LTRA	21 085	6.7
LAMA alone	15 897	5.1
LABA alone	10 738	3.4
ICS alone	10 368	3.3
LABA + LAMA	8 051	2.6
Relievers		
SABA alone	8 730	2.8
SAMA alone	5 639	1.8
SABA + SAMA	303	0.1
Exacerbation/infection markers		
Antibiotics	55 810	17.9
OCS	27 399	8.8
Other		
H1-antihistamines (systemic)	73 391	23.5
Expectorant (systemic)	24 857	8.0
Xanthine	8 475	2.7
Cough suppressant (systemic)	4 691	1.5
Cough suppressant with expectorant (systemic)	81	0.0
Anti-Immunoglobulin E	5	0.0

ICS: inhaled corticosteroids; LABA: long-acting beta2 agonists; LTRA: leukotriene receptors antagonists; LAMA: long-acting muscarinic antagonist; SABA: short-acting beta 2 agonist; SAMA: Short-acting muscarinic-antagonist; OCS: oral corticosteroids.

Figure 1 *- Flowchart of patients and prescriptions (adapted from Sá-Sousa et al. (17)).*

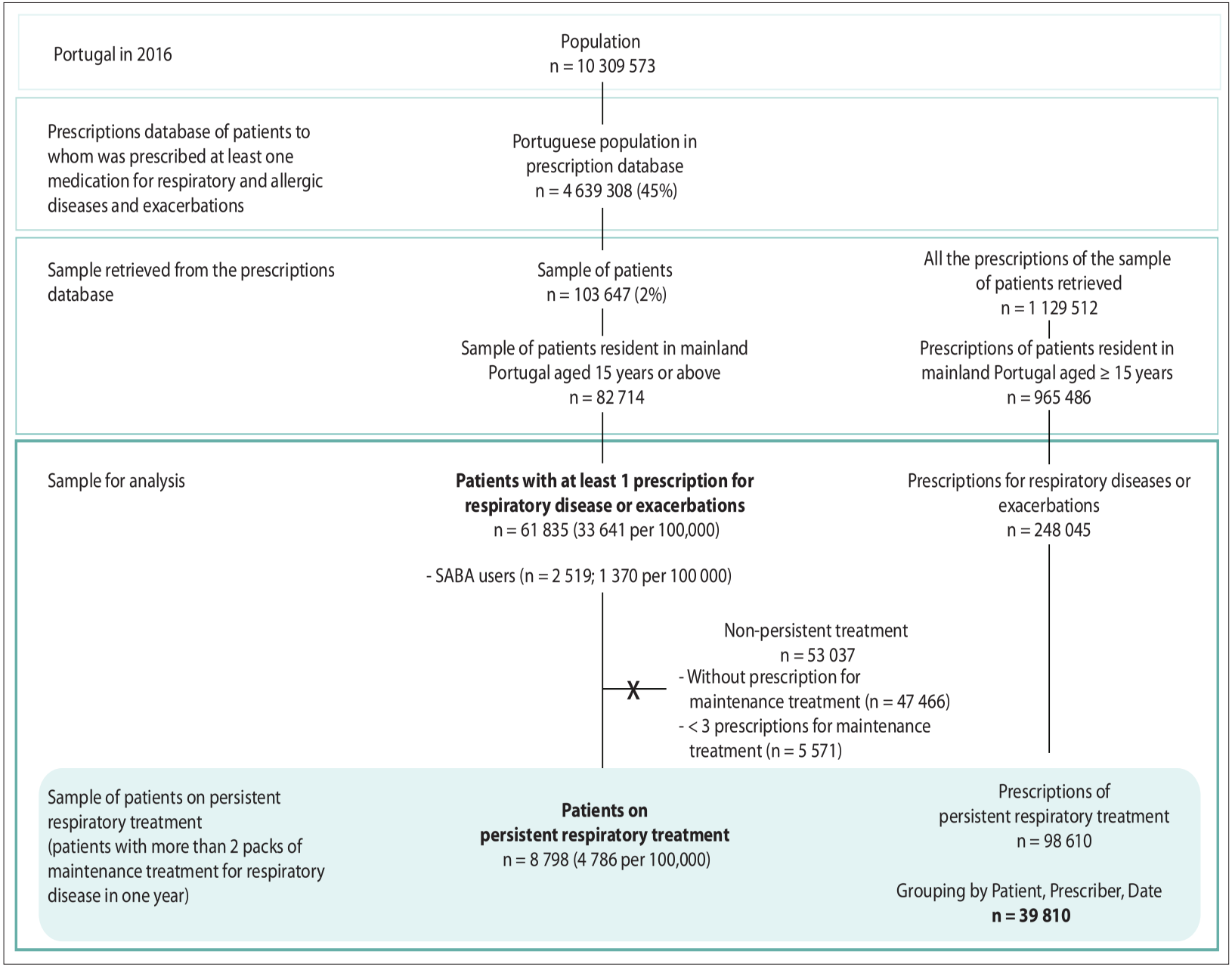


Table II *- Characteristics of the analysed prescriptions (n = 39810).*

	Total Column%, 95%CI	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10	Cluster 11
		(9,5%)	(6,6%)	(8,3%)	(6,0%)	(13,1%)	(7,6%)	(12,0%)	(5,8%)	(6,7%)	(14,2%)	(10,3%)
Age, med	68	74	63	66	75	68	63	70	44	72	63	66
P25-P75	52-78	64-82	47-76	48-79	65-82	52-78	47-74	58-80	30-59	63-80	50-78	49-77
Region												
South	45.4	8.7	7.7	8.3	6.0	10.2	6.7	12.4	7.6	6.7	14.0	11.6
	44.9-45.9	8.3-9.1	7.4-8.1	7.9-8.7	5.7-6.4	9.8-10.6	6.4.-7.1	11.9-12.9	7.2-8.0	6.4-7.1	13.5-14.5	11.1-12.0
North	32.4	11.0	5.6	9.2	4.1	15.3	7.6	12.6	4.4	6.6	14.2	9.5
	31.9-32.8	10.4-11.5	5.2-6.0	8.7-9.7	3.8-4.5	14.7-15.9	7.1-8.0	12.0-13.1	4.1-4.8	6.2-7.0	13.6-14.8	9.0-10.0
Centre	22.2	8.8	5.5	6.8	8.7	15.9	9.5	10.2	4.1	6.7	14.6	9.1
	21.8-22.6	8.3-9.5	5.1-6.0	6.3-7.4	8.2-9.3	15.2-16.7	8.9-10.1	9.6-10.9	3.7-4.5	6.2-7.2	13.8-15.3	8.5-9.7
Healthcare unit												
Primary care	48.3	11.0	0.3	7.8	5.7	22.7	12.4	14.6	0.0	6.5	19.3	0.1
	47.8-48.8	10.6-11.5	0.3-0.4	7.5-8.2	5.4-6.1	22.1-23.3	11.9-12.9	14.1-15.1	0.0-0.0	6.2-6.9	18.7-19.9	0.0-0.2
Secondary care	21.7	8.3	14.1	10.7	6.9	0.9	0.3	10.1	10.0	8.9	6.0	23.8
	21.3-22.1	7.7-8.9	13.4-14.9	10.1-11.4	6.4-7.5	0.7-1.1	0.2-0.5	9.4-10.7	9.4-10.6	8.3-9.5	5.5-6.6	22.9-24.7
Other	30.0	7.9	11.1	7.2	5.9	6.8	5.3	9.3	12.0	5.3	12.1	17.1
	39.6-30.4	7.4-8.4	10.5-11.7	6.8-7.7	5.5-6.3	6.4-7.3	4.9-5.7	8.8-9.8	11.4-12.6	4.9-5.7	11.5-12.7	16.4-17.7
Healthcare provider												
Public	69.7	10.1	4.6	8.7	6.1	15.8	8.6	13.1	3.1	7.3	15.1	7.5
	69.2-70.1	9.8-10.5	4.4-4.9	8.4-9.1	5.8-6.3	15.4-16.2	8.2-8.9	12.7-13.5	2.9-3.3	7.0-7.6	15.7-15.5	7.2-7.8
Private	30.3	7.9	11.0	7.2	5.9	7.0	5.4	9.4	11.9	5.3	12.2	16.9
	29.8-30.8	7.4-8.4	10.4-11.5	6.7-7.6	5.5-6.4	6.5-7.4	5.0-5.8	.9-10.0	11.3-12.5	4.9-5.7	11.6-12.8	16.2-17.6

Frequencies are summarized as row % and 95% Confidence Interval (95%CI), otherwise is indicated; P25-P75: Percentiles 25-75.

1. *Medication type* – active substances were classified in 14 medication types according to the International Non-proprietary Names: ICS plus LABA (ICS + LABA); LTRA; ICS alone; LABA alone; SABA alone; LAMA alone; LABA plus LAMA (LABA + LAMA); Xanthine; (short-acting muscarinic antagonists (SAMA) alone; SABA plus SAMA (SABA + SAMA). For a better understanding of the clinical sense of the clusters, we additionally included Antibiotics; OCS; H1-antihistamine (Anti-H1); nasal corticosteroids (nCS) and Expectorants combined or not with Cough suppressants in the analysis.
2. *Prescribers' specialties* – the specialties (n = 52) were grouped in general practitioners (GPs), pulmonologists, allergists, internists, and the other, less frequent, specialities grouped as "other".
3. *Packages* – number of packages of each medication type prescribed. In the BDNP system, it is possible to include several packages for each medication in the same prescription.

Additional external variables were analysed, such as the age of the patient; region of the prescription (mainland Portugal has 5 NUTS II regions that were recorded in 3: North, Center and South (Lisbon, Algarve and Alentejo)); Healthcare unit (primary care, secondary care or other) and healthcare provider (public or private).

Cluster analysis

Cluster analysis techniques were applied to identify prescription patterns based on medication and specialty of the prescriber using a two-step approach. The variables included in the final model were medication type (ICS + LABA; LTRA; ICS alone; LABA alone; SABA alone; LAMA alone; LABA + LAMA; Xanthine; SAMA alone; SABA + SAMA); and the specialty of the prescribers (GPs; pulmonologists; allergists; internist; other). In the first step, an automatic clustering algorithm estimated the number of clusters that best fitted the data, based on the Bayesian Information Criterion. This estimate was then used for the clustering analysis based on log-likelihood distance measures (18). We selected the parameters for which the model had the highest quality, and the final model had a silhouette coefficient of 0.5. The presence of additional medication (Antibiotics, OCS, anti-H1, nCS and expectorants combined or not with cough suppressants) was explored for each cluster.

Statistical analysis

Categorical variables are presented as absolute frequencies and proportions and 95% Confidence Interval for proportion (95% CI). Age differences between clusters were tested by Kruskal-Wallis chi-square. Statistical significance was set for a P-value of less than 0.05.

IBM SPSS Statistics 25 was used to conduct the two-step cluster analysis and RStudio 1.1.456 (https://rstudio.com/) for pre-processing and other analyses.

Results

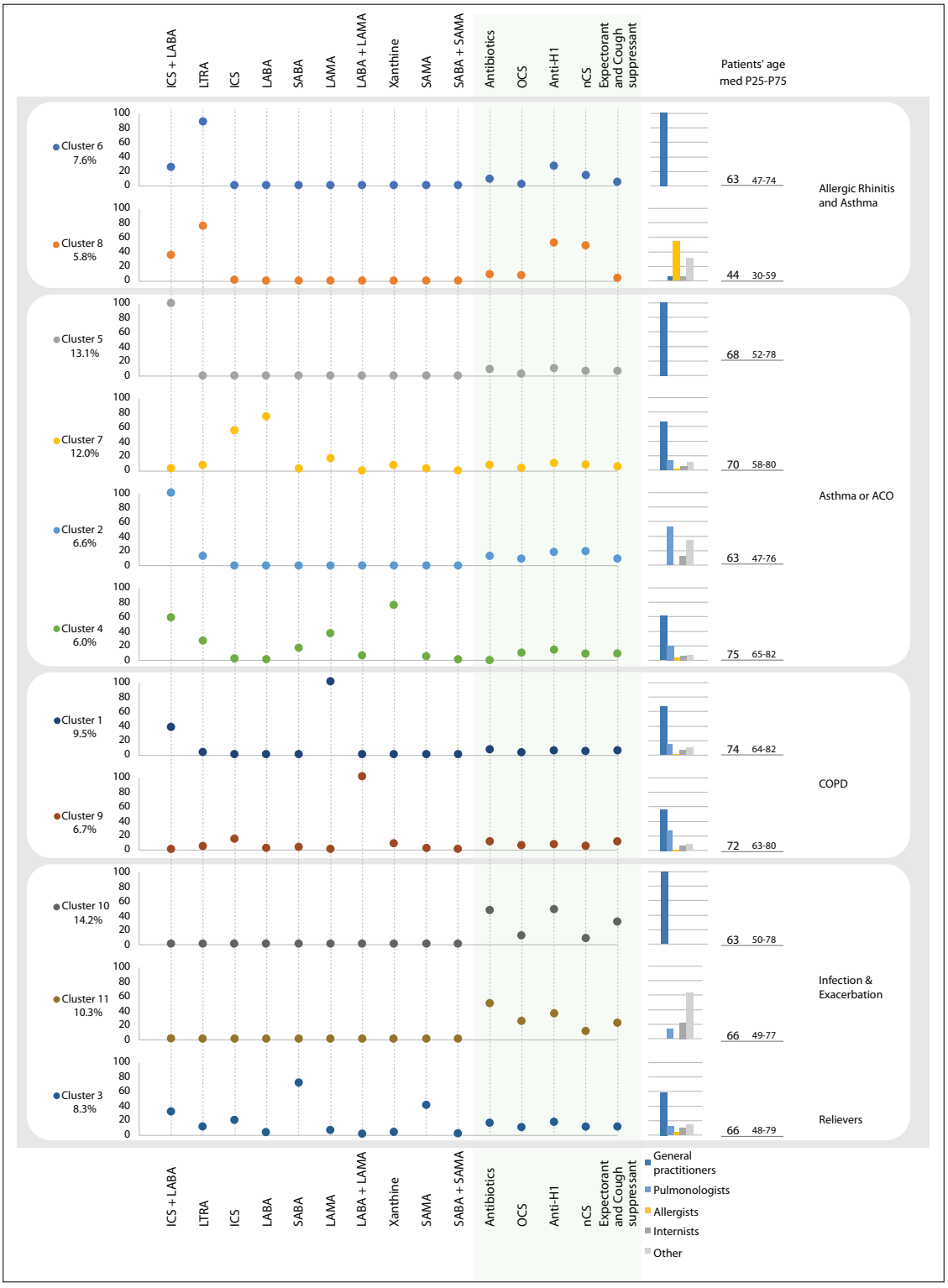
A total of 39810 prescriptions of PRT (**figure 1**) were registered in 2016 for the analysed sample, corresponding to 312527 packages (**table I**). Maintenance treatment represents 1/3 of the prescribed packages, mostly for ICS + LABA (11.8%) and LTRA (6.7%). Globally, the most prescribed drugs were H1-antihistamines (23.5%) and antibiotics (17.9%).

The cluster analysis conducted to assess prescription patterns based on medication and specialty of the prescriber, revealed that an eleven-cluster model was the solution that best fitted our data. The characteristics of prescriptions and external variables are described in **table II**. The most frequent prescription patterns are grouped in clusters 10 and 5, prescribed exclusively by GPs, and in clusters 7 and 11, written by prescribers with different specialties. The clusters' characteristics are summarized in **figure 2** and **online supplements table IS**. Additional medication (Antibiotics, OCS, anti-H1, nCS and expectorants combined or not with cough suppressants) and patients' age are also presented for each cluster.

Regarding external variables (**table II**), Cluster 8 was the pattern prescribed to youngest patients ($p < 0.001$) and clusters 1 and 4 to the oldest ($p < 0.001$). At primary care units and public healthcare providers, the most frequent prescriptions are grouped in Cluster 5 or 10, whereas secondary healthcare services and private providers prescriptions are grouped in cluster 11 more often. Based on the clinical interpretation of the medication in each cluster, including patients' age, they were grouped into four subsets, as follows:

1) *Medication for possibly Allergic Rhinitis and Asthma*:
   Clusters 6: prescriptions for LTRA alone or combined mostly with ICS + LABA. Additional frequent medications were H1-antihistamine (anti-H1) and nCS. Prescribed GPs for patients with a median age of 63 years old.
   Cluster 8: prescriptions for LTRA alone or combined mostly with ICS + LABA. Additional frequent medications were anti-H1 and nCS. Prescribed by allergists for patients with a median age 44 years old.
2) *Medication for possibly Asthma or ACO*:
   Clusters 5: prescriptions for ICS + LABA fixed combination, prescribed exclusively by GPs for patients with a median age of 68 years old.
   Cluster 7: prescriptions for ICS, LABA and LAMA. Prescribed mostly by GPs for patients with a median age of 70 years old.
   Cluster 2: prescriptions for ICS + LABA alone or combined with LTRA, and additionally includes prescriptions for anti-H1 and nCS. Prescribed mostly by pulmonologists for patients with a median age of 63 years old.
   Cluster 4: prescriptions for ICS + LABA, Xanthines, LAMA and LTRA. Prescribed mostly by GPs for patients with a median age of 75 years old.

Figure 2 *- Frequency of each prescription cluster (%) determined by 2 step cluster analysis and distribution of medication types, prescribers' specialities and age of the patients in each cluster. The distribution of additional medication, not included in the model, is presented in shadow.*



3) *Medication for possibly COPD*:
   Cluster 1: prescriptions for LAMA alone or combined with ICS + LABA. Prescribed mostly by GPs for patients with a median age of 74 years old.
   Cluster 9: prescriptions for LABA + LAMA alone or combined with ICS. Prescribed mostly by GPs and pulmonologists for patients with a median age of 72 years old.
4) *Medication for infection, exacerbation and relievers of symptoms*:
   Cluster 10: prescriptions for antibiotics, OCS, anti-H1, nCS and expectorants with cough suppressants, with no maintenance treatment. Prescribed exclusively by GPs for patients with a median age of 63 years old.
   Cluster 11: prescriptions for antibiotics, OCS, anti-H1, nCS and expectorants with cough suppressants, with no maintenance treatment. Prescribed mostly by specialties not related to respiratory diseases for patients with a median age of 66 years old.
   Cluster 3: prescription mainly for SABA, SAMA, but also with ICS + LABA, ICS, LTRA and LAMA. Prescribed mostly by GPs for patients with a median age of 66 years old.

Discussion

Eleven different prescriptions patterns clusters were revealed by unsupervised analysis based on medications and prescribers' specialties, and these clusters were grouped in four, based on the theoretical therapeutic indications of the medications and patient's age in each cluster.

Comparing the clusters obtained by unsupervised analyses with the pharmacotherapy recommended in relevant guidelines for asthma (1), COPD (2), and allergic rhinitis and asthma (19), we found that they have clinical relevance. According to Global Initiative for Asthma (GINA), in a stepwise approach, if the response to the treatment is suboptimal, it is recommended to intensify the treatment, either by increasing the dose of currently used ICS and adding another controller medication, such as LABA, LTRA, and xanthines. On the other hand, Allergic Rhinitis and its Impact on Asthma (ARIA) (19) recommends the treatment with nCS with either anti-H1 or LTRA for seasonal allergic rhinitis. Cluster 6 and 8, are profiles that closely resemble the GINA and ARIA recommendations for allergic asthma and rhinitis.

Guidelines advise different COPD initial treatments depending on the severity of symptoms, exacerbations, and airflow limitation (2). It consists of a bronchodilator, either SABA or SAMA or LABA or LAMA and LABA or LAMA; and, if the symptoms persist, both LABA + LAMA or ICS + LABA. For more severe cases the recommended initial therapy is LAMA + LAMA or, in patients with a history suggestive of asthma-COPD overlap or based on eosinophilic counts, ICS + LABA. The higher level of pharmacological care corresponds to triple therapy with LAMA + LABA + ICS or add-on of phosphodiesterase-4 inhibitor or a macrolide. Clusters 1 and 9 are profiles matching GOLD recommendations for COPD management.

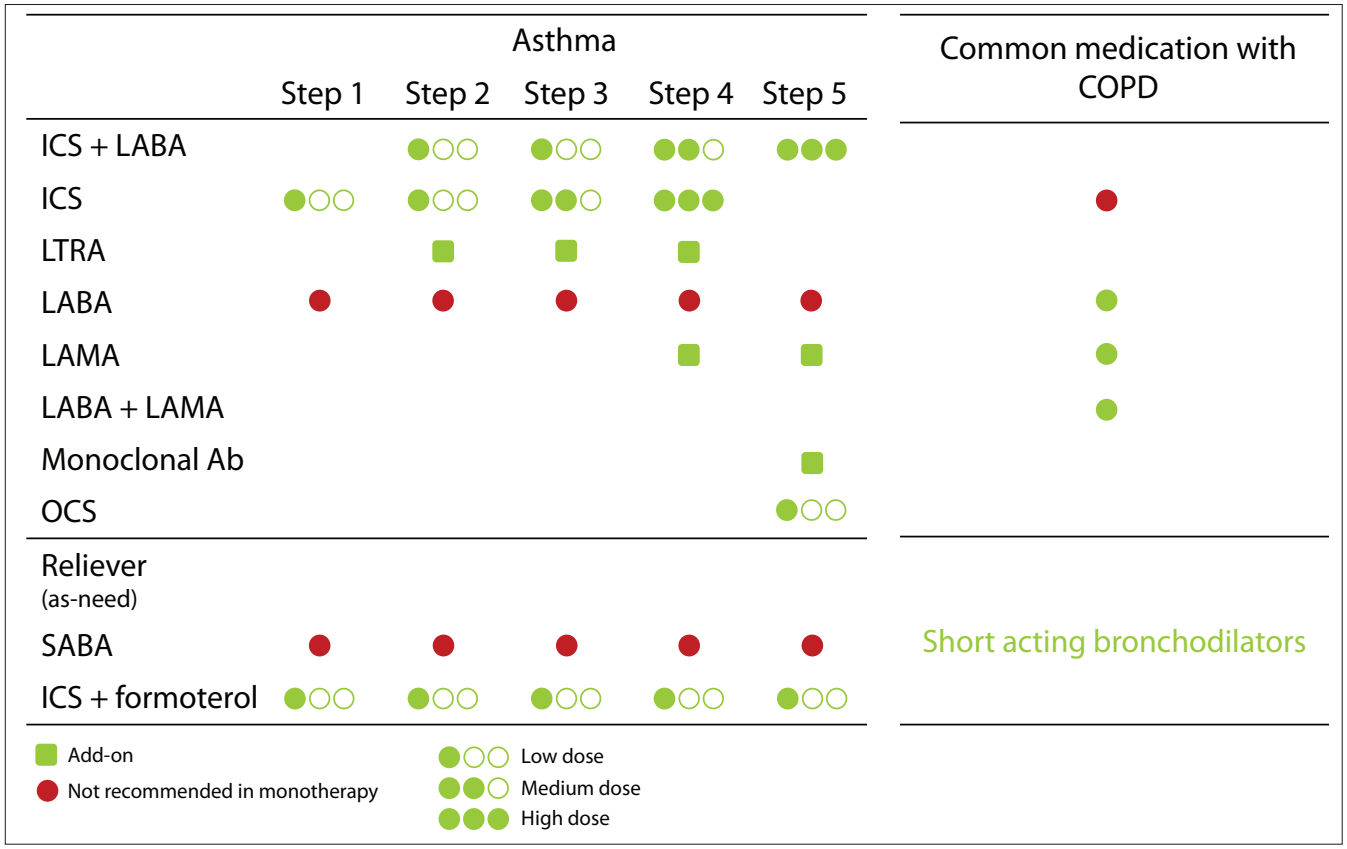
COPD therapeutic options have similarities with asthma treatment (**figure 3**). The higher level of asthma care corresponds to treatment with a high dose of ICS + LABA and the add-on LAMA, Immunoglobulin E (IgE), a low dose of OCS or biological therapy (1). The GINA recommendations for treating patients with features of both asthma and COPD is ICS in a low or moderate dose and add-on treatment with LABA and/or LAMA. Clusters 2,4,5 and 7 are mixed profiles corresponding to medication for possible asthma or ACO.

Until 2019, GINA recommended the use of SABA as the first line of asthma treatment (20). The recently published guide for asthma management by the GINA network, recommends that ICS should be used whenever SABA is used, and ICS combined with formoterol may be used in low dose as a reliever option (**figure 3**) (1). Cluster 3 describes a profile corresponding to rescue medication for asthma and COPD; clusters 10 (exclusively prescribed by GPs) and 11 (mostly prescribed by specialties not related to respiratory diseases) are profiles for exacerbations and infection treatment. This indicates that in some clinical visits, patients on PRT only receive a prescription for infections and exacerbations and that the use of some of these medications may be related to other comorbidities.

Studies that use prescription claims as proxies for diagnosis of asthma and COPD, based on *a priori* established algorithms, are controversial. Weidinger *et al*. used a representative sample of patients registered in primary healthcare units in Sweden to show that there was a large discrepancy between the proportion of patients with medication for asthma and COPD (SABA, LABA, ICS, and fixed combinations of ICS + LABA) with the proportion of patients with a formal diagnosis for asthma or COPD (5). These results indicate that the use of prescriptions as a proxy for the diagnosis may not be accurate. However, another study on Dutch children diagnosed with atopic diseases reported that having two or more prescriptions for asthma, including ICS can be a reliable proxy for asthma (6). A systematic review of studies on the classification of asthma severity using claims data stated that no best theory-driven algorithm has been established so far (7).

On the other hand, unsupervised methods, not based on *a priori* assumptions, bring new insight into the identification of patterns clinically relevant and with several applications. Slobbe *et al*. have shown that unsupervised methods applied to medication claims, may be used to predict the prevalence of six diseases, including asthma and COPD (21). Another study used clustering methods to establish different profiles of patients based on airflow limitation and explore its characteristics, namely in terms of medication prescribed in each cluster of adult patients with mild-to-moderate airflow limitation from the Korean National Health and Nutrition Examination Survey (16). Clustering methods have also been used to explore adherence barriers among respiratory patients, towards personalized care. A study using clusters based on adherence to inhalers in COPD patients, shown that certain de-

Figure 3 *- Medication used in asthma management and common medication with COPD.*



mographic and clinical measurements, including lung function, cough and cognitive impairment, were determinants for different profiles of adherence (22). To the best of our knowledge, there are no studies using unsupervised methods with similar methodology and variable to support our results.

This was the first analysis of the patterns of respiratory medication in the official Portuguese prescription database. Nevertheless, the present study has several limitations. The main limitation is related to the lack of information regarding treatment indication and duration of the treatment. Although we obtained prescription patterns with clinical relevance for asthma and COPD identification, having the diagnosis would allow the validation of the clustering method. Moreover, adding the indication could raise evidence on the medications commonly used for different indications and also used as off-label in the real-world. The duration of the treatment is also important for patient profiling, especially for exacerbation markers such as antibiotics and OCS. As with any data-driven clustering, there are limitations in the interpretation of derived classes as being a true set of clinically meaningful subgroups (9).

Finally, despite the large size of the analysed sample, it may not be representative of the Portuguese patients' population, because we were not able to analyse the complete dataset of the BDNP.

The clusters encountered in this study may be useful to explore primary adherence differences between patterns of prescriptions and also to compare with OTC (Over-the-counter) patterns. To address the goals of management of chronic respiratory diseases, besides giving the appropriate prescription for each condition, factors such as adherence to the treatment and use of over-the-counter medication need to be optimized. RWD has contributed to a better understanding of primary nonadherence (23, 24) and to raise awareness on the use of OTC medication for relievers of asthma symptoms (25). However, OTC uses of medication are not registered on the BDNP database and to the best of our knowledge, there is no data available on OTC medication for respiratory diseases in Portugal. In the future, studies on primary adherence, and also on OTC medication may uncover important barriers to adequate management of disease in the Portuguese population.

Conclusions

This study was based on prescription claims and revealed 11 prescription patterns for respiratory medication. These patterns could be grouped into four profiles medication for possibly: 1) Allergic Rhinitis and Asthma, 2) Asthma or ACO, 3) COPD, and 4) infection, exacerbation and relievers of symptoms medication and according to the prescribers' specialties. This profiling is the first step to understand the Portuguese reality on the prescribing of respiratory medication.

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Conflict of interests

The authors declare that they have no conflict of interests.

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Table IS *- Distribution of medication types and prescriber specialities by prescription clusters, determined by 2 step cluster analysis.*

Clusters	1	2	3	4	5	6	7	8	9	10	11
Medication type, %											
ICS + LABA	37.1	100.0	32.0	57.8	100.0	25.3	1.9	36.4	0.0	0.0	0.0
LTRA	2.8	11.7	11.2	26.8	0.0	100.0	7.5	75.1	4.7	0.0	0.0
ICS	0.0	0.0	20.3	1.3	0.0	0.0	54.8	0.9	14.9	0.0	0.0
LABA	0.0	0.0	3.7	1.0	0.0	0.0	74.2	0.0	2.0	0.0	0.0
SABA	0.0	0.0	71.2	15.9	0.0	0.0	2.9	0.0	3.4	0.0	0.0
LAMA	100.0	0.0	5.2	36.7	0.0	0.0	16.7	0.0	0.9	0.0	0.0
LABA + LAMA	0.0	0.0	1.1	6.1	0.0	0.0	0.0	0.0	100.0	0.0	0.0
Xanthine	0.0	0.0	2.7	75.7	0.0	0.0	6.8	0.0	8.7	0.0	0.0
SAMA	0.0	0.0	40.6	4.1	0.0	1.4	1.7	0.1	1.4	0.0	0.0
SABA + SAMA	0.0	0.0	1.9	0.5	0.0	0.0	0.1	0.0	0.2	0.0	0.5
Antibiotics	6.4	12.1	16.7	0.0	8.1	8.3	6.8	9.3	10.8	46.3	49.4
OCS	3.7	8.4	10.1	9.4	2.3	2.0	3.4	7.7	5.2	12.1	25.1
AntiH1	5.8	17.8	17.0	13.0	9.8	26.0	10.2	52.3	6.3	48.3	34.9
nCS	4.2	19.3	10.6	8.1	6.4	13.0	7.7	49.1	4.2	8.2	10.5
Expectorant and Cough suppressant	6.1	9.0	10.3	8.0	5.7	5.0	5.0	4.0	10.5	31.5	21.6
Prescriber specialty, %											
General practitioners	66.3	0.0	58.5	60.5	100.0	100.0	67.3	0.0	56.4	100.0	0.0
Pulmonologists	15.3	52.7	11.9	20.1	0.0	0.0	13.2	6.3	27.4	0.0	13.2
Allergists	1.0	0.0	4.1	4.6	0.0	0.0	1.8	55.2	0.3	0.0	0.0
Internist	7.0	13.0	10.3	6.4	0.0	0.0	5.9	6.2	6.7	0.0	23.0
Other	10.4	34.3	15.3	8.4	0.0	0.0	11.8	32.3	9.1	0.0	63.8