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A Classification System for Decision-Making in the Management of Patients with Chronic Conditions

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Abstract: Patients with chronic diseases are frequent users of healthcare services. The systematic use of stratification tools and predictive models for this group of patients can be useful for health professionals in decision-making processes. The aim of this study was to design two new classifier systems for detecting the risk of hospital admission for elderly patients with chronic conditions. In this retrospective cohort study, a set of variables related to hospital admission for patients with chronic conditions was obtained through focus groups, a health database analysis and statistical processing. To predict the probability of admission from the set of predictor variables, a logistic regression within the framework of Generalized Linear Models was used. The target population consisted of patients aged 65 years or older treated in February 2016 at the Primary Health Care Centre of Burjassot (Spain). This sample was selected through the consecutive sampling of the patient quotas of the physicians who participated in the study (1000 patients). The result was two classification systems, with reasonable values of 0.722 and 0.744 for the area under the ROC curve. The proposed classifier systems could facilitate a change in the current patient management models and make them more proactive.

Keywords: management of chronically ill patients; primary care; risk assessment; long-term care; decision-making; older people; screening; classification systems

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1. Introduction

Technological and scientific advances have produced a society with a high percentage of elderly people and patients with chronic diseases; these patients are frequent users of a variety of healthcare services, including hospital centers [1]. This group of patients usually receives fragmented, incomplete and ineffective care, which leads to an avoidable and unnecessary use of resources [2]. As a result, healthcare costs associated with the long-term care of this group of patients have risen [3], putting at risk the sustainability of long-term care insurance systems [4], and their management has become increasingly complex. In this regard, the European Commission has recognized the difficulty of decision-making for patients requiring long-term care [5]. In order to estimate these effects, it is necessary to use technological tools and new classification systems to support decision-making and design roadmaps, particularly in community, hospital and residential care [6].

In recent years, integrated care programs, which provide interdisciplinary interventions and follow-ups for patients with chronic diseases, have been a priority for health systems [7–9]. These programs are generally based on a model of patient-centered care (PCC), which is increasingly present in international healthcare policies due to its positive impact on patients and its potential to reduce healthcare costs [10,11]. Integrated care programs begin with early detection using stratification tools, encouraging different types of interventions throughout the disease cycle: the prevention of deterioration, health promotion, the treatment of exacerbations, management and self-management, long-term care, rehabilitation, and palliative care [12–14]. In this regard, integrated care strategies require stratification and classification tools for the purpose of individualizing care (customization) according to the risk, which in turn leads to a superior quality of care and higher levels of satisfaction for both patients and professionals [15–17]. In the Valencian Region of Spain, programs such as Valcronic have been developed in order to provide integrated care in a real-life context. This comprehensive program was aimed at patients with chronic conditions and incorporated telemonitoring applications (TMAs), including home-based telemedical measurement and input devices, in the management of these patients, as well as the introduction of stratification tools within health information systems [18]. More recent studies, such as the ATMoSPHAERE study [19], show that TMAs not only improve patient care but also allow the creation of cross-sectoral communication platforms for general practitioners, therapists, social services and multimorbid older patients. Recently, TMAs have been used for the home care of patients with COVID-19, and they have shown that the provision of home care can help to reduce the overloading of hospitals and decrease mortality rates [20]. The systematic use of stratification tools and predictive models can be useful and supportive for health system professionals in decision-making processes on different levels of the healthcare continuum [21].

After this Introduction, the paper has five remaining sections. The second one includes related works in the literature that have addressed the identification of patients and the prediction of risk, pointing out possible gaps and establishing the objective of the research carried out. The third section is devoted to the methodological procedure used in the study, including information about the data used and variables considered to which logistic regression has been applied to define two classification models. Section 4 presents the obtained results, and finally, Sections 5 and 6 focus on explaining the achieved results and comparing them with other works, pointing out the limitations of the study and the main conclusions and future lines of work.

2. Related Work

Numerous studies in the existing literature have sought to build tools whose purpose is to identify at-risk patients according to different output variables, such as the risk of future hospital admission [22–24], risk of fragility [25,26], risk of death [27,28] and risk associated with specific diseases [29–32], including the prediction of critical cases of COVID-19 [33]. These tools use predictive models to identify the relationships between different factors that allow the assessment of risks or associated probabilities based on a set of conditions; these guide the decision maker during organizational operations and require close cooperation between analytical teams, healthcare practitioners and patients [34]. This approach identifies sub-populations with comparable health risks, using healthcare data extracted from electronic health registries, to tailor interventions for those who will benefit the most [35]. Within the application framework, healthcare experts are currently using predictive analysis primarily to determine which patients are at risk of developing certain conditions or recurrent diseases. These predictive models can be complemented with descriptive models. Descriptive models allow us to quantify the relationships between data and are often used to classify patients—for example, by sorting them into categories—according to their disease or age group. These systems can be used to develop new, additional models that can mimic a large volume of individual agents and make predictions. These types of models have been applied to optimize the use of limited health resources, such as hospital admission, in crisis situations, such as those resulting from COVID-19 [36].

Most of the risk models of future hospital admission have been developed within the health systems of the US, England, Australia and Canada, although other models have been developed for countries such as Switzerland, Scotland and Ireland. Among all models, most of them have used retrospective administrative data and have focused on patients aged 65 years or older [22]. However, there have been proposals whose target has been any patient between 18 and 100 years, for instance, the QAdmissions Score [23]. This latter score uses variables recorded by general practitioners related to demographics, lifestyle, chronic diseases, prescribed medication, clinical values or laboratory test results. Other models, in addition to health-related variables, also include social variables. For instance, the PEONY model [24] incorporates "social deprivation" based on census information as a factor of interest. However, all these variables are not always fully available as structured variables in health databases (e.g., ethnicity). In other cases, variables are included in different databases that are not always inter-connected (e.g., current prescribed medication and clinical values). Finally, it is worth noting that most models have not been validated in health systems different from those in which they were developed. For all these reasons, it is difficult to apply most of the existing risk detection tools in health systems in a standardized way.

In any case, the early identification of patients at risk of hospital admission can facilitate the implementation of interventions that would save potential costs related to the consumption of care resources [37], thus contributing to the sustainability of the health system, and so preventing and/or reducing functional decline and deterioration in the quality of life of the elderly [38].

The above literature review evidences the successful use of risks models to address problems related to hospital admission prediction. However, the following research gaps were observed:

- Most models cannot be calculated using only routine health data that are systematically available in health databases.
- In a previous study, the authors implemented stratification instruments, originally developed and validated in other countries, in a Spanish sample of older people. The results demonstrated a moderate efficiency in the identification of patients at risk of hospital admission when using these stratification instruments [39].

Therefore, the goal of this work was to present two new classification systems for the detection of older patients at risk of hospital admission, developed in the Spanish healthcare system. The designed models use structured variables available in the databases of the healthcare system and can be calculated automatically. The models improve the level of the risk detection of other instruments validated in Spain, which use a small number of variables, such as the Community Assessment Risk Screen [39]. These models could be used by primary care teams and case management teams, in addition to hospitals. Their application would allow these stakeholders to carry out future proactive actions to reduce or avoid hospital admissions.

3. Materials and Methods

In this retrospective cohort study, the focus group technique was used to agree on the list of potential variables to be included in the patient stratification model. For 2 months, a multidisciplinary panel composed of six primary care experts from the Valencian healthcare system (physicians, nurses and social workers) with experience in care for chronicity and in long-term care was convened. Each session lasted approximately 90 min and took place in the Burjassot Primary Health Care Centre. Burjassot, located in the Valencian Community (Spain), is a municipality with 37,324 inhabitants as of 2016. It is part of Health Department 5. The sessions were conducted by two researchers with previous experience in stratification models and, after receiving the panel's consent, the conversations were recorded with a digital recorder. Once the variables were selected, a retrospective cohort study was carried out using the health information system. The study was approved in 2014 by the Ethical Clinical Research Committee (ECRC) of Arnau de Vilanova Hospital (Valencia, Spain).

3.1. Target Population and Sample

The target population consisted of patients aged 65 years or older, treated in February 2016 at the Burjassot Primary Health Care Centre.

The pilot sample consisted of 1000 patients. This sample was selected by the consecutive sampling of the patient quotas of the physicians who participated in the study.

The exclusion criteria were: (a) having an age under 65 years; (b) lacking data in the electronic health information systems; (c) neither having a permanent residence in Burjassot nor being institutionalized there; (d) having a planned hospital admission in the next 12 months and/or not being associated with the diagnosis of a chronic disease; and (e) exitus.

3.2. Data Collection

The data on the independent variables, with a reference date of February 2016, were collected by primary care professionals through the Abucasis information system (a medical record for primary healthcare). The processed data were anonymized to protect the personal data of the patients. Finally, a search for the minimum basic set of data (on the hospital information system) was performed to detect the hospital admissions planned for each patient in the subsequent 12 months. The dataset is available as supplementary material to this paper (Dataset S1).

3.3. Selected Variables and Statistical Analysis

We considered the admission of a patient as a response variable. These variables were calculated using the Bernouilli distribution, with two possible values: 0, meaning no admission, and 1, meaning admission. Explanatory variables were used to evaluate the effect on the probability of admission (see Table 1): those were sex, age, presence of respiratory diseases, presence of heart diseases, presence of dementia diseases, presence of chronic pain, presence of palliative care, presence of hemiplegia, presence of diabetes, number of visits to the hospital emergency service, number of visits to the emergency service at the Primary Care Centre, number of visits by emergency services at home, number of calls to the emergency service of the Primary Care Centre, total number of diseases and total number of emergency service uses. Table 2 describes the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes corresponding to the variables related to diseases.

Table 1. Variables used in the study.

Variable	Description
Admission (response)	0 = No (899), 1 = Yes (101)
Sex (explanatory)	M = Male (363), F = Female (637)}
Age (explanatory)	Between 64 and 101
Respiratory diseases (explanatory)	0 = No, 1 = Yes
Heart diseases (explanatory)	0 = No, 1 = Yes
Dementia diseases (explanatory)	0 = No, 1 = Yes
Chronic pain (explanatory)	0 = No, 1 = Yes
Palliative care (explanatory)	0 = No, 1 = Yes
Hemiplegia (explanatory)	0 = No, 1 = Yes
Diabetes (explanatory)	0 = No, 1 = Yes
Number of visits to the hospital emergency service (explanatory)	0, 1, 2, 3, ...
Number of visits to the emergency service at the Primary Care Center (explanatory)	0, 1, 2, 3, ...
Number of visits by emergency services at home (explanatory)	0, 1, 2, 3, ...
Number of calls to the emergency service of the Primary Care Center (explanatory)	0, 1, 2, 3, ...

Table 2. ICD-9MC used to identify diseases of interest to the study.

Diseases	ICD Code
Respiratory diseases	40—Bronchitis not specified as acute or chronic 491—Chronic bronchitis 492—Emphysema 493—Asthma 494—Bronchiectasis 495—Extrinsic allergic alveolitis 496—Chronic airway obstruction
Heart diseases	402—Hypertensive heart disease 410—Acute myocardial infarction 411—Other acute or subacute forms of ischemic heart disease 412—Old myocardial infarction 413—Angina pectoris 414—Other forms of chronic ischemic heart disease 425—Cardiomyopathy 427—Cardiac dysrhythmias 428—Heart failure
Dementia	290—Dementias 294.1—Dementia in diseases classified elsewhere 294.2—Dementia not specified 331—Other brain degenerations 780.93—Memory loss
Chronic pain	338.2—Chronic pain 338.3—Pain (acute) (chronic) related to a neoplasm
Palliative care	V66.7—Convalescence and palliative care
Hemiplegia	342—Hemiplegia and hemiparesis
Diabetes	250—Diabetes mellitus

Taking into account that the object of this study was to predict the probability of admission from a set of various predictor variables, a logistic regression within the framework of Generalized Linear Models [40] was used.

A generalized linear model is made up of a linear predictor:

$$\eta_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_p X_{pi}$$

and a link that describes how the mean of the response variable (the probability of the admission):

$$E(Y_i) = \mu_i$$

depends on the linear predictor (the set of the predictor variables):

$$g(\mu_i) = \eta_i$$

In the particular case of logistic regression, the usual link (from which the name of the model is derived) is the logit:

$$g(\pi_i) = \text{logit}(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right)$$

where $E(Y_i) = \pi_i$ is the probability of a positive outcome (an admission in our case).

All the possible combinations of the explanatory variables used produced a large list of different model structures. Among them, a model comparison procedure was used to select the best classification system for the admission—that is, the system that best predicted the probability of a positive outcome. In particular, all the resulting model structures were fitted and first compared on the basis of the Akaike Information Criterion (AIC) [41] in order to find the best model to explain the data observed. Next, the area under the receiver operating characteristic curve [42] was used to find the best predictive model. The curve was created by plotting the true positive rate (also known as the sensitivity) against the false positive rate (also obtained as one minus the specificity) at various threshold settings. As a result, the area under the curve offered a good explanation of the ability of the resulting models to correctly classify the possible admissions.

The leave-one-out cross-validation (LOOCV) method was used for the purpose of the evaluation. In the LOOCV method, one case is left out as the testing set, and the rest of the data are used as the training set. This process is repeated so that each case is in one iteration the testing case. The adjusted cross-validation estimate of the prediction error was calculated.

All the analyses were performed using the R software [43].

4. Results

The selection of the best classification systems was performed in two different versions. One was a simplified version which only included the age, gender, number of diseases (total.diseases) and total number of emergency service uses (total.urgencies). The other was a more detailed version that included all the variables presented in Table 1. The results of the inference on the logistic regression parameters for the indicator have been included as supplementary material (Tables S1 and S2).

In the first case, the best model selected in terms of both the AIC and the area under the receiver operating characteristics (AUROC) was a model with a linear predictor (Indicator 1):

$$\eta_i = -3.206 + 0.659 * \text{total. diseases} + 0.089 * \text{total. urgencies}$$

The indicator obtained in the second situation had as its linear predictor (Indicator 2):

$$\begin{gathered}\eta_i = -3.127 + 0.436 * \text{RESP} + 0.776 * \text{CARD} \\ +0.672 * \text{chronic.pain} + 1.142 * \text{palliative.care} \\ +1.620 * \text{hemiplegia} + 0.402 * \text{diabetes} \\ +0.202 * \text{number.hospital.urgencies} \\ +0.525 * \text{number.home.urgencies}\end{gathered}$$

As can be observed in Table 3, when comparing both indicators, the second demonstrated better results, although the use of the first indicator may be very convenient due to its simplicity. Indeed, this was the reason the latter was considered. In both cases, the area under the receiver operating characteristic curve (ROC curve) had a reasonable value.

Table 3. Measures of the performance of the two classification systems proposed.

Model	Indicator 1	Indicator 2
Residual deviance	599.71	578.51
AIC	605.71	596.51
Area under ROC curve	0.722	0.744

For both indicators, the probability of admission can be obtained by means of the inversed logit transformation:

$$\pi_i = \frac{\exp(\eta_i)}{1 + \exp(\eta_i)}$$

Being able to predict the probabilities of admission to hospital can be a very helpful tool for practitioners. As an example, using Indicator 1, the probability of the admission of a patient with two previous uses of the emergency services and two diseases can be estimated to be 0.15.

In line with this, health managers could classify patients in a fixed number of groups, depending on their probability of admission. For instance, they could be divided into three groups:

- Level 1, low risk of admission: probability of admission < 0.1.
- Level 2, medium risk: probability of admission between 0.1 and 0.2.
- Level 3, high risk: probability of admission > 0.2.

Tables 4 and 5, respectively, show the percentage of admissions for the three categories for both indicators in the dataset analyzed in this study. As can be observed, in both models there was a total of admissions of around 5% for the patients classified as low risk. This percentage increased to 17% in those patients classified as medium risk in both cases. Finally, 27% of the patients classified as high-risk with the first indicator were admitted to hospital, while this percentage was close to 36% with the second indicator.

Table 4. Admissions observed in the dataset after classifying patients with the first indicator at three levels of risk.

Admission	Level 1	Level 2	Level 3
Yes	37	36	28
No	658	167	74
Percentage	5.3%	17.7%	27.5%

Table 5. Admissions observed in the dataset after classifying patients with the second indicator at three levels of risk.

Admission	Level 1	Level 2	Level 3
Yes	36	32	33
No	682	158	59
Percentage	5.0%	16.8%	35.9%

The LOOCV prediction error estimation was calculated for the null model and for the models related to both indicators. The prediction error of the null model was 1.000, while for the fitted models of Indicator 1 and Indicator 2 it was 0.343 and 0.320, respectively. These results show the improvement obtained by using these indicators in comparison to the absence of patient information.

5. Discussion

The classification models we designed focused on primary care patients, in the same line as models such as QAdmission [23] developed in England using NHS data; we also used logistic regression, as in the case of the PEONLY model [24] and the prediction model of Marcusson et al. [44]. The models incorporate retrospective data collections, although there are other models that include primary data collected in real time, such as the survey-based model developed by Hasan et al. in the US [45]. In our analysis, age and sex did not appear as variables that influenced hospital admission within the pilot study carried out in the Valencian healthcare system. These two variables are considered by other instruments already validated, such as the Probability of Repeated Admission (PRA), which have been tested in patients from the Valencian Community [37] or others such as PEONY, developed in Scotland [24], that are not validated in the Spanish healthcare system. The PRA is a tool used in research and clinical practice to predict re-admission (more than once) within four years for elderly people [46]. This instrument includes eight factors found to be the strongest indicators of future hospital admission: age, gender, general self-reported health, history of diabetes or coronary heart disease, previous physician visits or hospital admissions in the previous year and caregiver availability [47]. This tool uses a regression equation—developed by the Johns Hopkins University—that weighs the responses to each survey question to provide an overall score between 0.07 and 0.80.

The variables "number of visits to the emergency service at the Primary Care Centre" and "number of calls to the emergency service of the Primary Care Centre" were not significant in the models we considered. In the subsequent analysis, the professionals justified this fact by pointing out that the hospital's emergency department was able to resolve most of these cases and that further interventions were not usually required. Another variable that had no influence on hospital admissions was "dementia"; in these cases, the patient is usually overseen by their physician and does not usually generate emergency hospital admissions. Among the most relevant variables were heart disease, palliative care and hemiplegia. However, in the variable "hemiplegia", we consider that its relevance was linked to the small number of cases that appeared in the sample.

This study concludes with the proposal of two classification systems: a simplified version, which only included the total number of diseases and the total number of emergency services uses; and a more detailed version, which included eight variables (respiratory diseases, heart diseases, chronic pain, palliative care, hemiplegia, diabetes, number of visits to hospital emergency services and number of visits to emergency services at home). Other classification methods, such as random forest, naive bayes, neural networks or SVM could be used to produce these indicators with similar results. Furthermore, Bayesian hierarchical models with random effects could be explored in order to obtain more complex indicators using additional patient and health system information. The development of more complex indicators should be consistent with the two proposed indicators, following a scalability criterion.

The advantages of the two proposed models are their simplicity, given the small number of variables, and the ease of access to data, since those are available in the digital databases of the healthcare system. In this sense, the classification system becomes proactive, since the risk information is available for the physician's reference in the computerized primary care system [48]. This last feature is not always present in other models, such as the model proposed by Maleki et al. [49], which consists of only four questions, including some that are posed directly to the patient/caregiver, such as "does the patient need help with using general transport?"; the Hippisley-Cox and Coupland model [23], with 30 variables, including information not systematically collected in medical records, such as "alcohol status", "smoking status" and "ethnicity"; and the model developed in Spain by Martínez et al. [50] that includes the variable "mean nursing care pressure of the primary care team" and "Charlson index" that each require a previous calculation. Other models are more complex and include more variables, as they try to detect the risk of short-term hospital re-admission within, for example, 30 days of discharge, such as PARR-30 [51].

6. Conclusions

This study features some limitations. The main limitation is that the sample was only taken from one health department in one Spanish region. It was not possible to apply it to new databases. Nonetheless, the proposed classification systems allow the design of new programs and measures to care for this group of patients, optimizing the use of resources in the healthcare system. The impact of the proposed tools on the healthcare system would have positive consequences for annual budget distributions (such as a reduction in hospital expenditure) and for the implementation of good-quality active and healthy aging policies, as well as for the satisfaction of patients and caregivers.

The proposed risk classification systems for hospital admission could be used to balance the number of patients among professionals, depending on the extent and magnitude of care that patients require. In that respect, we consider that the influence on the outcome variable (hospital admission) is linked to the characteristics of the group of patients assigned to each professional. In the Spanish healthcare system, each professional has a stable medical quota, whose characteristics of age, chronicity, functional deterioration, and fragility can directly influence the probability of future hospital admissions. This factor could be analyzed in more detail to establish compensation criteria for professionals, avoiding the concentration of at-risk populations within the care of a small number of physicians, or at least reducing their quotas according to the aforementioned types of characteristics.

Risk classification systems could be connected to artificial intelligence (AI) tools in the future; these would allow access to patients' data and a customized provision of long-term care services. The tools proposed in this paper can be easily integrated into intelligent systems, based on AI, to support decision-making related to the care and management of chronic older patients, applying predictive analytic techniques. The predictive analysis brings a variety of mathematical and statistical techniques of modeling, machine learning and data mining to analyze current and historical real data to make predictions about the future or unknown events, in order to anticipate the behavior and properties of the resulting care pathways. The development of these systems requires the collaboration of different stakeholders in addition to health providers, such as technology companies and interdisciplinary research teams. Although the research trend in the field of chronic care is to maintain continuous monitoring of each patient (promoting a continuity between health and social care), there do not exist in Spain AI tools to identify chronic patients, analyze the use of health services and propose integrated care pathways. This is one of the research topics on which the authors are working with international teams.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su132313176/s1: Dataset S1, Dataset used in the study; Table S1, Results of the inference on the logistic regression parameters for indicator 1. Estimates, standard errors and *p*-values; Table S2, Results of the inference on the logistic regression parameters for indicator 2. Estimates, standard errors and *p*-values.

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Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Arnau de Vilanova Hospital, Valencia, Spain (protocol code 813006, 2014).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available in the Supplementary Materials.

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