Predicting 15-day unplanned readmissions in hospitalization departments: an application of logistic regression

Prediciendo reingresos hospitalarios no planificados antes de 15 días: una aplicación de la regresión logística

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ABSTRACT

Hospital readmission is considered a key research area for improving care coordination and achieving potential savings. This is important because hospital readmissions can have negative consequences in terms of good health and recovery for patients. It is thus important to significantly reduce such readmissions. Unfortunately, there isn't a one-size-fits-all solution to preventing hospital readmissions. There are many variables outside of hospitals' direct control, such as social determinants and patient lifestyle factors, impacting readmissions. Although several studies have been undertaken to investigate 30-day readmissions, predicting revisits in shorter intervals (e.g., within 15 days after discharge) is highly needed to capture hospital-attributable returns better and develop more effective improvement plans. Hence, the aim of this paper is three-fold: i) to develop a comprehensive experimental study for identifying factors affecting 15-day readmission risk, ii) to classify patients according to the risk of 15-day readmission using logistic regression, and iii) provide general recommendations to reduce the 15-day readmission risk considering different predictors. To this end, the patients' characteristics were first described. Then, the significance of potential predictors, their interactions, and their effects were assessed. After this, a logistic regression model was derived to predict the likelihood of 15-day readmission in each patient. Finally, general recommendations were provided to reduce 15-day revisits. A real case study in Colombia was considered to validate the proposed methodology.

Keywords: Hospital readmission, logistic regression, quality of care, health policy.

RESUMEN

El reingreso hospitalario es considerado como un área de investigación clave para mejorar la coordinación del cuidado y lograr ahorros potenciales. Esto es importante debido a que los reingresos hospitalarios pueden tener consecuencias negativas en términos de la buena salud y recuperación de los pacientes

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del sector público y privado. Por tanto, los hospitales han decidido trabajar significativamente para reducir tales reingresos. Desafortunadamente, no hay una solución universal para prevenir reingresos hospitalarios. Hay muchas variables por fuera del control directo de los hospitales tales como los determinantes sociales y factores de estilo de vida del paciente que pueden impactar los reingresos. Aunque diversos estudios han sido aplicados para investigar las readmisiones en periodos menores a 30 días, predecir reingresos en intervalos más cortos (Por ejemplo, 15 días) es altamente requerido para detectar aquellos reingresos que son atribuibles a los hospitales y desarrollar entonces planes de mejora más efectivos. Por tanto, el propósito de este artículo es triple: i) desarrollar un estudio experimental para identificar los factores que afectan el riesgo de readmisión a los 15 días siguientes, ii) clasificar pacientes de acuerdo con el nivel de riesgo utilizando regresión logística y iii) proveer recomendaciones generales para disminuir el riesgo de reingreso a los 15 días siguientes considerando diferentes predictores. Para esto, se describieron inicialmente las características de los pacientes. Luego, se evaluó la significancia de predictores potenciales, sus interacciones y efectos. Después de esto, se generó un modelo de regresión logística para predecir la probabilidad de reingreso de un paciente a los 15 días siguientes al alta. Finalmente, se produjeron recomendaciones generales para reducir estos reingresos. Un caso de estudio real en Colombia fue considerado para validar la metodología propuesta.

Palabras clave: Readmisión hospitalaria, regresión logística, calidad del cuidado, política de salud.

INTRODUCTION

Hospital readmissions (or, in other words, a subsequent hospital admission within a specified period following an original admission) have been increasingly used as an outcome measure for assessing the performance of the health care system[1, 2, 3, 4]. Of course, the ability to predict patient readmission risk is extremely valuable for hospitals. Revisits often occur, but they are not easily predictable. Developing national benchmarks for hospital readmissions can help identify those patient populations with relatively high readmission rates. According to the *American Agency for Healthcare Research and Quality*, in 2011, there were approximately 3,3 million 30-day all-cause hospital readmissions in the United States, and they were associated with about $41,3 billion in hospital costs [5]. Among the ten major causes of 30-day readmission for Medicare patients aged 65 years and older are congestive heart failure, cardiac dysrhythmias, acute and unspecified renal failure. In turn, for Medicare patients aged between 18 and 64 years, some of the major causes of readmission are mood disorders, alcohol-related disorders, pregnancy complications. A complete and systematic review was carried out to identify the causes of readmission [6]. In Colombia, there is little information on the problem [7]. Their research was undertaken to determine the frequency of 15-day all-cause hospital readmissions and associated factors. The major result was an increase in the hospital readmissions rate due to patients with circulatory system diseases. Such a study also calculated that, in Colombia, the costs derived from 15-day readmissions are approximately USD 21998275, which represents 15% of the total hospitalization expenses. On the other hand, the Colombian Ministry of Health and Social Protection identified that the average readmission rate was 9,46%, with a standard deviation of 26,96%, reflecting the poor performance of the hospitalization departments within this region.

In our opinion, the quantification and early identification of unplanned readmission risk have the potential to improve the quality of care during hospitalization and post-discharge. However, high dimensionality, sparsity, class imbalance of electronic health data, and the complexity of risk quantification, challenge the development of accurate predictive models [8]. There is a variety of factors involved in hospital readmissions, many of them unpredictable. It is then essential to monitor the vital signs and clinical status to detect and select the appropriate clinical intervention [9, 10]. Hospital readmissions can have negative consequences for patients and are costly for both public and private payers [11]. It is necessary to explore how to make the right decision under uncertainty [12]. Identifying conditions that contribute to most of the readmissions may help health care stakeholders decide which conditions should be targeted to maximize quality improvement and cost-reduction efforts.

The likelihood of readmission and associated contributing factors vary according to the post-discharge time length [13]. Thus, it is crucial to understand how readmission rates and the conditions associated with the highest readmission rates vary based upon different post-discharge time frames. Besides, early hospital readmissions within 15 days of discharge are common and costly. To this end, in our research, a statistical model based on logistic regression is proposed to predict the probability of readmission in hospitalization departments within 15 days. In detail, 101766 patients (11357 readmitted and 90409 non-readmitted) have been studied, taking into account 23 predictor variables (age, sex, marital status, homecare, number of medicines that the patient takes). The data were extracted from a health insurer. Considering the above-mentioned studies, the contribution of this paper is three-fold:

i) to develop a comprehensive experimental study for identifying factors affecting 15-day readmission risk,
ii) to classify patients according to the risk of 15-day readmission using logistic regression, and
iii) provide general recommendations to reduce the 15-day readmission risk considering different predictors.

The remainder of this paper is organized as follows. Background of the literature review already carried out on prediction modeling, and patient readmission is provided in Section 2. Section 3 explains the materials and method, and Section 4 describes the statistical analysis and data preparation. A discussion of the results is presented in Section 5. Finally, Section 6 summarizes the research contribution and findings.

STATE OF ART ON PREDICTION MODELING AND PATIENT READMISSION

Recently, interesting studies have analyzed the risk of readmissions in hospitals. For a comprehensive survey of the phenomenon, an investigation using the Scopus database, the largest abstract and citation database of peer-reviewed literature, was carried out. There are several peer-reviewed literature databases. However, the two most recognized in the scientific community are Scopus and Web of Science (WoS). In the present research, the Scopus database was used for institutional needs. It also provides a set of meta-data that are essential for the bibliometric analysis, such as abstracts, cited references, times cited, authors, institutions, countries, and the journal impact factor, which are not easily available in other databases.

Furthermore, it is easy to navigate, even for the novice user. Neither database is inclusive but complements each other. The choice, in general, is based on personal preference and institutional needs.

Regarding our specific scientific interest, we used the following search code "*readmission in hospitalization AND statistical model*." The search highlighted 659 publications from 1991 (the date on which the first document appeared) to 2018 (data updated to September 2018). It appears a growing interest in this specific topic, as shown in Figure 1.

As shown in Figure 2, the majority of documents are published in the USA, a result that is not a surprise. It is significant to note that published documents are divided as follows: 615 Articles, 17 Conference Papers, 25 Reviews, 1 Book Chapter, and 1 Article in press. To finalize our investigation, a more in-depth analysis of the documents has been carried out. According to the literature analysis, it is important to point out that some relevant studies supported the direct relationship between the quality of care delivered during patients' hospital stays and outcomes such as readmissions. Moreover, the emergency medical readmission dynamics is considered a focal point since the causes and the diseases that can bring patients at risk for hospital readmission are various.

Following, an overview of the most relevant publications related to our research is presented. Several factors were recently associated with unplanned readmission in diabetic foot ulcers (DFUs) patients treated in a multidisciplinary setting [14]. Two interesting studies were published in 2017. First, a logistic regression analysis was used to identify significant predictors of prolonged hospitalization ($\geq$15 days) and readmission [15]. The authors of the second study sought to determine the frequency, risk factors, and outcomes for patients experiencing post-discharge care fragmentation [16]. Another

Source: Scopus database.

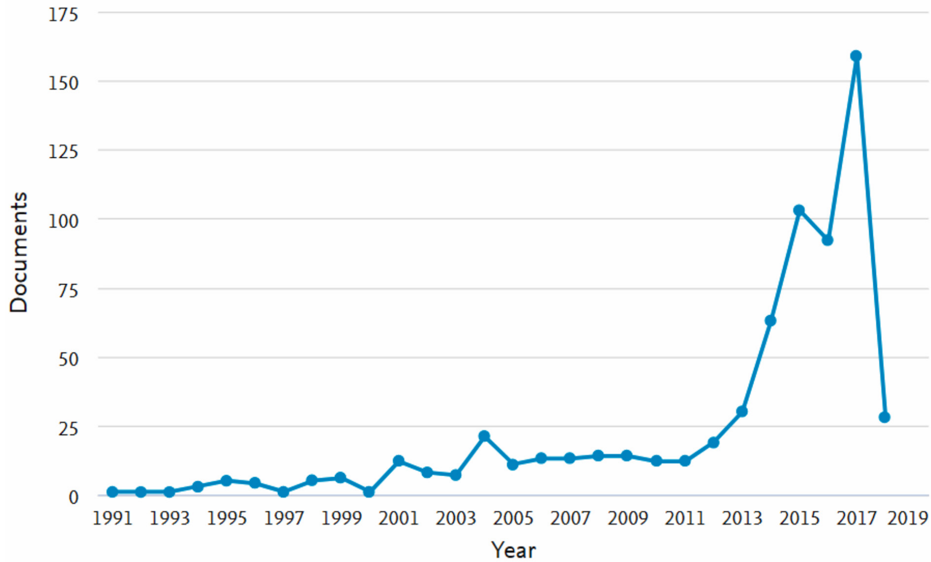

Figure 1. Documents by year.

Source: Scopus database

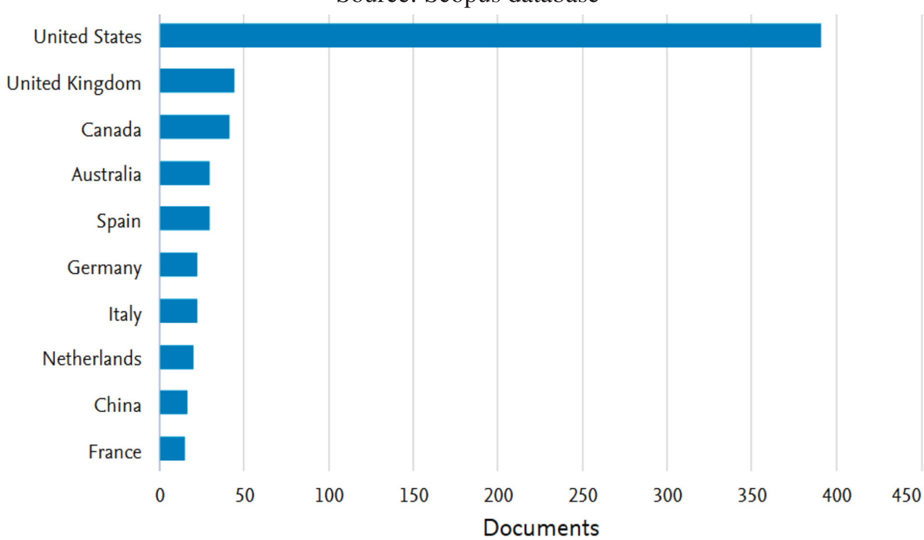

Figure 2. Documents by country/territory.

worthy study focused on identifying those patients who are likely to be readmitted to the hospital [17]. Previously, an investigation examined the influence of the number of discharge medications on the prevalence of thirty-day readmission [18]. Some other studies focus on predicting readmission for patients with a particular disease. For example, a study proposed the utility of the LACE index (The Length of stay, Acuity, Comorbidities, Emergency) to predict readmission or death in patients hospitalized with heart failure [19].

Moreover, other authors examined the role of reducing patient anxiety after discharge to prevent 30-day readmissions for kidney transplant recipients [20]. In 2006, the use of routine hospital data was evaluated to identify patients at high risk of emergency admission [21]. The most common methods used to predict readmission hospitalization are stepwise logistic regression and multivariate logistic regression [22]. This result is consistent with another study that described and compared several models for predicting early hospital readmissions [23]. The main result shows that the most frequently used methods are: 1) Logistic regression; 2) Logistic regression with multi-step variable selection; 3) Penalized logistic regression; 4) Random forest and 5) Support vector machine.

Some authors proposed a comparison among methods. For instance, a generic framework was proposed for institution-specific readmission risk prediction [24]. The authors declared that the institution-specific readmission risk prediction framework is more flexible and more effective than the one-size-fits-all models like the LACE, sometimes twice and three times more effective. Another study presented a retrospective multi-center model to predict hospital readmissions in a cohort of hospitalized children [25].

Furthermore, a logistic regression analysis was performed to identify significant predictors of unplanned readmission within 30 days of discharge to develop a scoring system for estimating readmission risk [26]. In 2008, a retrospective cohort was designed to develop and validate predictors of 30-day hospital readmission in patients with ages higher than 65 years using readily available administrative data [27]. Additionally, they compared prediction models that use alternative comorbidity classifications.

Reviewing previous studies clarifies that most previous research in predicting hospital readmissions are limited to applying a single predictive model, while our research aims to propose a holistic model. This study's novelty also lies in the fact that there are no previous reports on models that predict unplanned revisits within 15 days after discharge. Most of the related studies focus on 30-day readmissions. The advantage of using a shorter-term allows healthcare managers to react fastly to contingencies and consequently diminish the negative impact on patient outcomes and financial sustainability of hospitalization departments. This is complementary because shorter intervals can better reflect the hospital-attributable readmissions [28, 29]. Furthermore, general recommendations are provided to address the readmission risk considering different factors and interactions that have not been reported in the literature.

METHODS

Data extraction

The case study presented in this paper reflects the concern relating to the readmission rate in a healthcare provider's hospitalization departments located in Colombia. On average, the overall readmission rate stood at 9.46%, thereby exceeding the upper specification limit established by the Ministry of Social Protection and Health (Upper Specification Limit - USL = 5%), representing a warning signal for this institution in terms of quality. The average length of stay (ALOS) also increased by 76.7%, which caused a wider use of medical staff in this provider. Moreover, it was determined that preventable readmissions significantly contributed to rising healthcare costs. A statistical model was designed to measure the likelihood of 15-day readmissions in hospitalization departments to address this problem. With this probability, patients can be classified into a risk category, and prevention plans can be created for each patient to reduce that probability. Socio-demographic and health variables were taken into account, considering the results from the previous literature review. The data we used was an extract representing 10 years of UIS (User Information System) reports from more than 100 hospitals. Additional data were collected during a 5-10 minute telephone interview. The database contains a total of 49 features associated with 74036643 visits to hospitalization departments. After pre-processing the data, 25 features (patient code, 1 response variable, and 23 potential predictors) were finally retained for further analysis.

Encounter selection

A set of admissions was rigorously selected, considering the following conditions:

i) It refers to a patient whose family members could be interviewed to obtain data associated with social status,
ii) The encounter is associated with a patient who was not discharged home, i.e., a patient who was transferred to another healthcare provider,
ii) The laboratory tests were completed during the last stay, and he medicines were administered

during the last stay. The criterion i) was used to remove admissions with no available data for the social domain, which is an area of interest in this study. On the other hand, condition ii) was applied to exclude readmissions whose medical care was not exclusively provided in the origin hospital; while, criteria iii) and iv) helped us retain readmissions associated with low quality of care. The initial data file contained incomplete, repeated, and noisy information as expected in any real-world data source. Finally, 101766 admissions were proved to meet these conditions and were then selected for further analysis.

Outcome variable and Predictors

The outcome defined for this analysis is a binary variable where "1" represents that the patient was readmitted to the hospitalization department within 15 days of hospital discharge, and "0" means both "readmission after 15 days" and no readmission. The focus on a restricted 15-day window is based on the fact that this is a metric to evaluate the overall performance and possibly penalize hospitalization departments for excessive unplanned readmissions [30]. It is then necessary to identify the most contributing factors [31]. In this regard, four types of potential predictors were defined from the literature review and medical experts to be associated with readmission risk: demographic, social status, healthcare system, and health status of the patient. Figure 3 illustrates the potential predictors and classifies them according to the aforementioned categories. Each potential predictor was operationally defined to provide a comprehensive understanding of the model. In the Demographic category, AGE (A) factor refers to the patient's age measured in years. Sex (S) was set as a binary variable where "0" means "Male" and "1" means "Female." In the Social category, Marital Status (MS) was defined as a 4-point scale where "0" means "Single", "1" means "Married", "2" means "Divorced" and "3" means "Widow." Regarding the Healthcare System category, both "Homecare (H)" and "Monitoring Visits" were also defined as binary variables. In the "Homecare" factor, "0" means the patient was referred to a homecare program, while "1" represents that has been admitted to the hospitalization department. In the "Monitoring Visits (MV)" factor, "0" signifies that the patient has been visited to have his/her health status checked, while "1" means the opposite.

Considering the health status of patient category, "Body Mass Index (BMI)" was also set as binary variables where "0" signifies "Abnormal"; while "1"

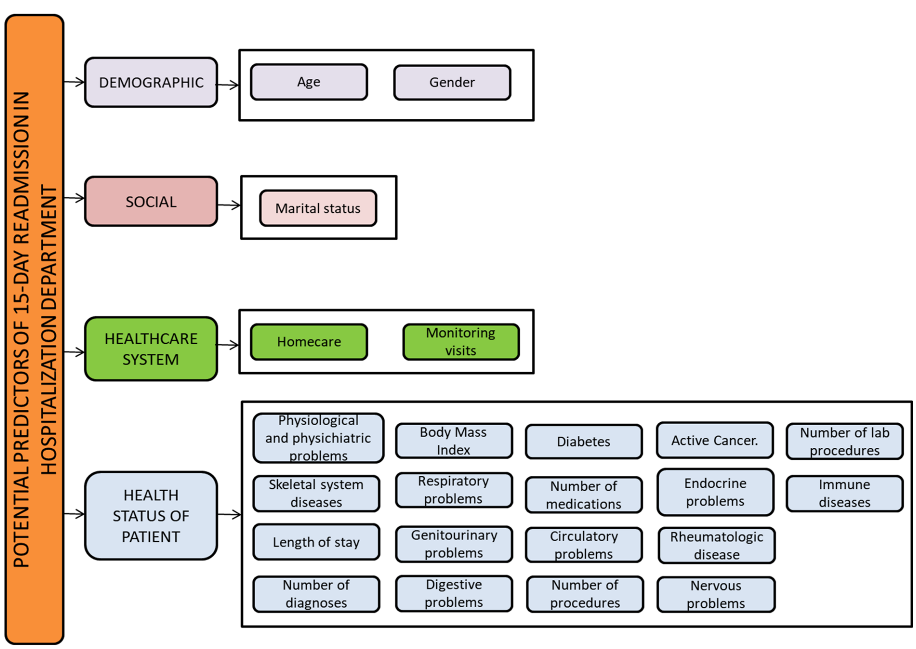

Figure 3. Potential predictors of 15-day readmission in hospitalization department.

means "Normal." Factors related to specific diseases ("Respiratory Problems (RP) ", "Genitourinary Problems (GP)", "Digestive Problems (DP)", "Circulatory Problems (CP)", "Active Cancer (AC)", "Endocrine Problems (EP)", "Nervous Problems (NP)", "Skeletal System Diseases (SSD)", "Psychological and Psychiatric Problems (PPP)", "Genitourinary Problems (GUP)", "Diabetes (D)", "Rheumatologic Disease (RD)" and "Immune Diseases (ID)" were also categorized as binary variables where "0" indicates that the patient has not experienced that kind of disease; while "1" denotes the opposite.

Furthermore, "length of stay (LOS)" denotes the average duration that a patient stayed in the hospitalization department (inpatient days are calculated by subtracting the day of admission from the day of discharge). "Number of Medications (NM)" refers to the number of medicines a patient currently takes due to his/her medical treatments. On the other hand, the "Number of Diagnoses (ND)" factor refers to the number of present diseases that are simultaneously in a patient. "Number of Lab Procedures (NLP)" was also deemed to represent the number of lab tests that were performed before readmission. Finally, Number of Procedures (NPC) denotes the number of surgeries a patient has had.

Statistical Analysis

In this case, the patient was the unit of analysis. The logistic regression was used to better model the probability of 15-day readmission in terms of the predictors mentioned above. This was done to provide a better prediction of the outcome variable. The detailed procedure of logistic regression can be found in Boateng and Abaye [49]. All statistical analyses were conducted using the Minitab 17® software. A summarized version of the methodology applied in this work is described in Figure 4.

First, the selected sample of patients was characterized. Next, the significance of the potential predictors was evaluated. Here p-values and coefficients were calculated for each factor. The p-values < 0.01 factors were considered as statistically significant and categorized as "predictors"; while the other factors (P-value ≥ 0.01) were discarded. On the other hand, factors with positive and negative coefficients were identified and graphed separately using a bar diagram. Coefficients close to 0 indicate that the association between the potential predictor and the response is not important. These procedures were introduced to pinpoint the predictors most contributing to increase or diminish the likelihood of readmission in the hospitalization department within 15 days of hospital discharge. The logistic regression model was then created, taking into account the factors that were proved to be significant. The predictors' values of each patient were then applied in the logistic regression model to validate its predictive ability in terms of prediction error. Afterward,

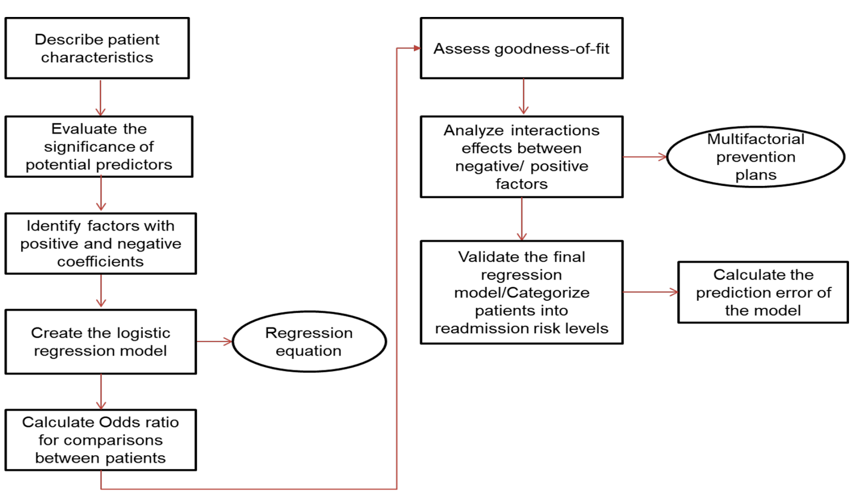

Figure 4. The proposed methodology for the prediction of readmissions in the hospitalization department within 15 days of hospital discharge.

odds ratios (OR) were calculated using the logit link function. This was done to compare patients who had a particular condition with those who did not have it. The goodness of fit was assessed by using Pearson and deviation chi-squared tests. P-values close to 1 denote that the model fits the data adequately.

Interaction effects were also analyzed and plotted to identify significant interactions between factors. This was relevant to propose effective multifactorial prevention plans to reduce readmission rates in these hospitals [32, 33]. The logistic regression model's output can be later used to categorize the patients into a readmission risk level: 0 (Low risk) and 1 (High risk).

Ethical and legal aspects

The study here is based on datasets extracted from the User Information System (UIS) containing no personally identifiable information. Given the de-identified nature of the dataset, the ethical committee determined that this research was exempt from formal approval.

RESULTS

Description of patient characteristics

- **Demographic and social predictors:** Age distribution for this sample can be illustrated in Table 1 (μ = 65.97 years; *M* = 68 years). It is shown that 65.37% of the patients are older than 60 years old. Also, a high number of readmissions (n = 23720) were related to the "old adult" category. Additionally, 97.21% of the patients belong to "intermediate adult" and "old adult" categories. On the other hand, *sex* was almost equally distributed in the sample (Male: 46.24%, Female: 53.76%). Most of the admissions in this category are related to female patients (n = 19518). Regarding *marital status*, most of the patients were married (40.64%). Particularly, 15923 readmissions are linked to this condition.
- **Factors related to the healthcare system:** Regarding factors related to the health status of the patients, 87.22% of the patients were hospitalized at home, and 66.16% were continuously monitored after initial medical attention (refer to Table 1). In detail, 30145 of the readmissions refer to patients who were discharged to homecare.
- **Factors related to the patients' health status:** The mean length of stay was 4,4 days and *M* = 4 days (refer to Table 1). Also, it can be indicated that the average number of medications taken by the patients is 15 and *M* = 16 medications. Interestingly, the average number of lab procedures during hospital stay was 43.1 with *M* = 44 procedures. Also, the number of comorbidities in the sample was approximately 8 (average). Considering the presence of specific diseases, only 0.99% of the patients experienced respiratory problems; 77% suffered from diabetes mellitus; close to 20% had been diagnosed with obesity problems while the percentage of ill patients with other diseases do not get over 6%.

Significance of potential predictors

Using Minitab 17® software, significance tests were performed to evaluate if the potential factors could be considered predictors of readmission in hospitalization departments within 15 days of hospital discharge. The P-values and t-statistics are shown in Table 2.

The results of these tests evidenced that "Length Of Stay", "Respiratory Problems", "Immune Disease", "Genitourinary Problems", "Digestive Problems" and "Rheumatologic Diseases" were statistically non-significant for the outcome variable (p-value > 0.01) and should be then removed from the predictive model and discarded for further analysis. The factors most contributing to the probability of readmission were those with P-value = 0.

Figure 5a and 5b evidence factors with positive and negative coefficients in the logistic regression model. There are predictors with a meaningful contribution to the probability of readmission within 15 days In both graphs. This is important to design-focused prevention plans for both hospitals and patients. Regarding significant predictors with negative coefficients, "Monitoring Visits" was ranked in 1st place with a coefficient of -0.7561. Considering significant predictors with positive coefficients, "Endocrine Problems" (2.510) and "Skeletal System Diseases" (0.5469) are the most contributing factors. Figure 6 illustrates the main effects plot for each predictor compared to the response PR (15 days).

Table 1. Characterization of variables and readmissions (sample size: 101766 admissions).

Factor	Levels	Table	% of the population	Number of readmissions
Sex	Male	47058	46.24%	16027
	Female	54708	53.76%	19518
Marital Status	Single	30224	29.70%	9957
	Married	41316	40.60%	15923
	Divorced	14350	14.10%	5299
	Widow	15876	15.60%	4366
Homecare	hospitalized at home	88756	87.22%	30145
	not hospitalized at home	13010	12.78%	5400
Monitoring Visits	Monitored	67331	66.16%	23175
	Non-monitored	34435	33.84%	12370
Body Mass Index	Abnormal	81777	80.36%	28785
	Normal	19989	19.64%	6760
Respiratory Problems	Healthy patient	100761	99.01%	35170
	ill patient	1005	0.99%	375
Genitourinary Problems	Healthy patient	99468	97.74%	34694
	ill patient	2298	2.26%	851
Digestive Problems	Healthy patient	101191	99.43%	35328
	ill patient	575	0.57%	217
Circulatory Problems	Healthy patient	95874	94.21%	33488
	ill patient	5892	5.79%	2057
Active Cancer	Healthy patient	101211	99.45%	35381
	ill patient	555	0.55%	164
Endocrine Problems	Healthy patient	101479	99.72%	35482
	ill patient	287	0.28%	63
Nervous Problems	Healthy patient	101084	99.33%	35419
	ill patient	682	0.67%	126
Skeletal System Diseases	not experienced disease	99133	97.41%	34925
	ill patient	2633	2.59%	620
Physiological and Psychiatric Problems	Healthy patient	100803	99.05%	35246
	ill patient	963	0.95%	299
Diabetes	Healthy patient	23403	23.00%	7227
	ill patient	78363	77.00%	28318
Rheumatologic Disease	Healthy patient	101749	99.98%	35540
	ill patient	17	0.02%	5
Immune Diseases	Healthy patient	101756	99.99%	35539
	ill patient	10	0.01%	6
AGE	30 years old or younger	2839	2.79%	854
	30-60 years old	32400	31.84%	10971
	Older than 60	66527	65.37%	23720
Other Factors		**Mean**	**Median**	**1st Qu.**
AGE		65.97	68.00	55.00
Length of Stay		4.40	4.00	2.00
Number of Medications		16.02	15.00	10.00
Number of Diagnoses		7.42	8.00	6.00
Number of Lab Procedures		43.10	44.00	31.00
Number of Procedures		1.34	1.00	0.00

Table 2. P-values and coefficients of potential predictors.

Factor	Coefficient	P-value	Statistical significance
Age	0.0187	0.000	Significant
Number of procedures	0.049	0.000	Significant
Number of diagnoses	0.048	0.000	Significant
Monitoring visits	–0.7561	0.000	Significant
Length of stay	–0.0084	0.034	Non-Significant
Number of medications	–0.0067	0.000	Significant
Number of lab procedures	0.0067	0.000	Significant
Marital status	0.2866	0.000	Significant
Sex	0.1646	0.000	Significant
Homecare	0.3698	0.000	Significant
Respiratory problems	0.191	0.060	Non-Significant
Nervous problems	0.848	0.000	Significant
Circulatory problems	0.3415	0.000	Significant
Immune disease	–0.577	0.444	Non-Significant
Endocrine problems	2.510	0.000	Significant
Active cancer	0.427	0.000	Significant
Genitourinary problems	–0.053	0.401	Non-Significant
Skeletal system diseases	0.5469	0.000	Significant
Psychological and psychiatric problems	0.344	0.000	Significant
Diabetes	0.07	0.002	Significant
Body mass index	0.2896	0.000	Significant
Digestive problems	0.074	0.577	Non-Significant
Rheumatologic diseases	–1.088	0.088	Non-Significant

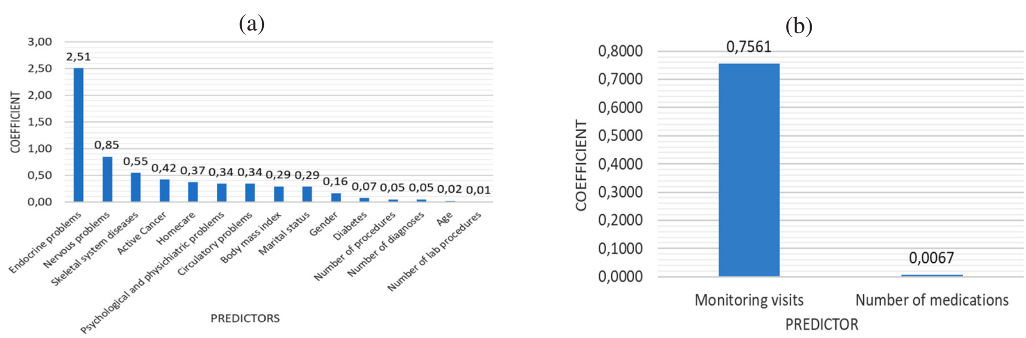

Figure 5. Predictors with a) positive and b) negative coefficients in the logistic regression model.

Creation of the predictive equation

The Predictive equation was determined based on binary logistic regression technique. The equation derived from this technique (refer to equation 1) is described as follows:

$$LnPR - 15\ day = 0{,}0067NLP - 0{,}0067NM + 0{,}2866MS + 0{,}1646G + 0{,}3698H + 0{,}848NP + 0{,}345C + 2{,}510EP + 0{,}427AC + 0{,}5459SSD + 0{,}344PPP + 0{,}07D + 0{,}2896BMI + 0{,}0187A + 0{,}049NPC + 0{,}048ND - 0{,}7561MV - 0{,}0016A * NP - 0{,}0016A * ND + 0{,}0072A * MV + 0{,}0072A * NLP - 0{,}0057A * MS - 0{,}0038A * G - 0{,}0038A * H - 0{,}0444A * EP - 0{,}0144A * SSD - 0{,}0092A * D - 0{,}0101A * BMI - 0{,}0088NP * LOS - 0{,}0496NP * ND + 0{,}005NP * NM + 0{,}0192NP * NLP - 0{,}058NP * MS - 0{,}0373NP * G - 0{,}1907NP * SSD - 0{,}1347NP * D + 0{,}1359ND * MV - 0{,}0036ND * NM - 0{,}0029ND * NLP - 0{,}0596ND * MS - 0{,}0383ND * G - 0{,}1705ND * H - 0{,}378ND * EP - 0{,}1168ND * SSD - 0{,}1321ND * PPP - 0{,}0744ND * D + 0{,}0171NM * NLP + 0{,}501NM * MS + 0{,}3561NM * G + 3{,}811NM * EP + 0{,}971NM * PPP + 0{,}3078NM * D - 0{,}0123NLP * MS - 0{,}0098NLP * G - 0{,}0148NLP * GP - 0{,}0136NLP * SSD - 0{,}0156NLP * D - 0{,}894H * SSD + 0{,}2216H * D + 0{,}365CP * D + 1{,}187SSD * D \quad (1)$$

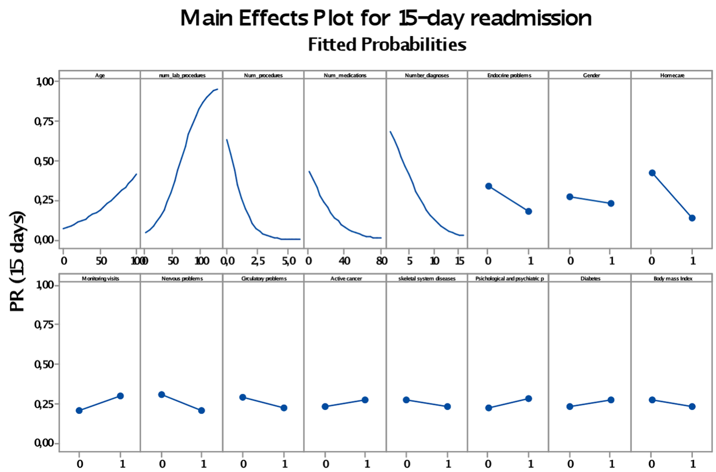

Figure 6. Main effects plot for readmission probability in hospitalization departments within 15 days of hospital discharge.

"PR - 15 day" represents the probability of readmission within 15 days of hospital discharge in the hospitalization department, and potential predictors have been explained in Sub-section "Outcome variable and predictors".

Odds ratios for predictors of 15-day readmission

It is necessary to calculate the odds ratio for each predictor of the logistic regression model using Minitab 17 ® software to establish multivariate comparisons between patients in terms of readmission probability. The odds ratios were calculated and are shown in Table 3.

On the other hand, Deviance chi-squared test was used to estimate how well the model fitted the data. In this case, a $\chi^2 = 71841.61$, DF = 101747 and p-value = 1.0 provide sufficient evidence to indicate that the model adequately fits the data. Moreover, based on the Hosmer-Lemeshow

Table 3. Odds ratios for predictors of readmission in hospitalization department within 15 days of hospital discharge.

Predictor	Odds ratio	99% Confidence interval
Age	1.0189	(1.0175; 1.0203)
Number of procedures	1.0518	(1.0335; 1.0705)
Number of diagnosis	1.0508	(1.0372; 1.0646)
Monitoring visits	0.4743	(0.4446; 0.5060)
Number of medications	0.9944	(0.9904; 0.9984)
Number of lab procedures	1.0070	(1.0056; 1.0083)
Marital status	1.3282	(1.2508; 1.4102)
Sex	1.1788	(1.1212; 1.2392)
Homecare	1.4441	(1.3261; 1.5725)
Nervous problems	2.3220	(1.5536; 3.4705)
Circulatory problems	1.3943	(1.2266; 1.5849)
Endocrine problems	12.3801	(4.8901; 31.3424)
Active cancer	1.3492	(1.1211; 1.5093)
Skeletal system diseases	1.7109	(1.4327; 2.0431)
Psychological and psychiatric problems	1.4430	(1.1087; 1.8780)
Diabetes	1.0725	(1.0107; 1.1382)
Body mass index	1.3343	(1.2436; 1.4316)

results, a good model fit can also be concluded (p-value = 0.688).

Interaction effects between factors

Table 4 shows the p-values and coefficients of the significant interactions (P-value < 0.01) between predictors concerning the readmission probability in the hospitalization department within 15 days of hospital discharge. These interactions are relevant to creating multivariate control and prevention plans to reduce the initial PR (15 days). Therefore, these analyses become strong decision-making support for managers and practitioners in healthcare prevention.

Validation of the final model and calculation of prediction error

Using the logistic regression model, a set of values (derived from the patients' characteristics) were assigned to each predictor as described in the Sub-section "Outcome variable and predictors" to validate the model and calculate the prediction error. It was possible to assign readmission risk levels according to the estimated readmission probabilities and scoring system described in "Statistical Analysis." The results of the validation process are presented in Table 5. In this case, 88997 patients (validation cohort) were categorized (test period = 3 months) into a risk level of readmission to validate the proposed model's effectiveness. In this case, the model's discrimination was excellent due to the area under the ROC curve was 0.81 (refer to Figure 7).

DISCUSSION

23 potential predictors for 15-day readmission probability in the hospitalization department were identified to ensure high prediction rates considering the literature review provided in this paper. This work considered **4 types of factors** (Demographic, Social, Healthcare System, and Health Status of patients), taking into both internal and external factors that may affect this performance indicator. In sample characterization, descriptive statistics were calculated to provide a comprehensive knowledge of the main features related to the patients considered in this study. An analysis of significant factors (p-value < 0.01) was then made considering their coefficients, odds ratios and, interactions to illustrate their contribution (positive or negative) to the probability of readmission within 15 days of discharge. Summing up, **14 factors** were found to have positive significant coefficients (refer to Figure 8). Here below is a discussion of the main results.

Endocrine problems

One of these predictors was "Endocrine Problems", whose C = 2.510 indicates that a patient suffering from endocrine diseases is more likely to be readmitted to the hospitalization department within 15 days if effective prevention programs are not deployed. This is also confirmed by an OR = 12.3801 (99% CI, 4.8901 - 31.3424), which specifies that a person with this illness has a probability of 12.3801 times larger of being readmitted than a patient who is not affected by this problem. It can also be pointed out that 2-order interactions, including "Endocrine Problems", were found to be significant. Specifically, when combined with "Number Of Medications", "Number of Diagnoses", and "AGE." Special attention should be paid to the interaction, including "Number of Medications", whose coefficient was found to be positive (3.811). This means that PR (15 days) is even larger when a patient with endocrine problems receives daily doses of different medications. This is based on the fact that when concurrent medication use, polypharmacy, and chronic conditions of patients interact, drug-related adverse events may appear, and immediate medical care is therefore needed to address patients' symptoms. These findings are also consistent with the reported literature [34, 35]. Another study pointed out that diabetes mellitus, hyperglycemia, and hypokalaemia are the endocrine diseases with the highest influence on increased readmission rates [36]. In this respect, diagnosis and monitoring errors at the earlier stages of endocrine diseases have been identified as the major causes of readmissions. Hence, it is important to provide high-quality primary care by ensuring the participation of endocrinologists who can adequately diagnose and treat patients by controlling, for instance, their glucose and potassium levels and administering the most suitable medications. Furthermore, it is important to provide effective outpatient care and monitoring to the patients while educating their families regarding the adherence to the recommended treatment plan, timely reporting unexpected changes in patients' condition, and emotional support.

Nervous problems

On the other hand, "Nervous Problems" was also concluded to have a positive coefficient C = 0.85,

Table 4. P-values and coefficients of the interaction terms calculated from the binary logistic regression model.

Interaction		Coefficient (C)	P-value
Age	Number of procedures	–0.0016	0.000
	Number of diagnoses	–0.0016	0.000
	Monitoring visits	0.0072	0.000
	Number of lab procedures	0.0072	0.000
	Marital status	–0.0057	0.000
	Sex	–0.0038	0.001
	Homecare	–0.0038	0.000
	Endocrine problems	–0.0444	0.000
	Skeletal system diseases	–0.0144	0.003
	Diabetes	–0.0092	0.000
	Body mass index	–0.0101	0.000
Number of procedures	Length of stay	–0.0088	0.000
	Number of diagnoses	–0.0496	0.000
	Number of medications	0.0050	0.000
	Number of lab procedures	0.0192	0.000
	Marital status	–0.0580	0.001
	Sex	–0.0373	0.002
	Skeletal system diseases	–0.1907	0.001
	Diabetes	–0.1347	0.000
Number of diagnoses	Monitoring visits	0.1359	0.000
	Number of medications	–0.0036	0.000
	Number of lab procedures	–0.0029	0.000
	Marital status	–0.0596	0.000
	Sex	–0.0383	0.000
	Homecare	–0.1705	0.000
	Endocrine problems	–0.378	0.002
	Skeletal system diseases	–0.1168	0.000
	Psychological and psychiatric problems	–0.1321	0.009
	Diabetes	–0.0744	0.000
Number of medications	Number of lab procedures	0.0171	0.000
	Marital status	0.5010	0.000
	Sex	0.3561	0.000
	Endocrine problems	3.811	0.000
	Psychological and psychiatric problems	0.971	0.000
	Diabetes	0.3078	0.000
Number of lab procedures	Marital status	–0.0123	0.000
	Sex	–0.0098	0.000
	Genitourinary problems	–0.0148	0.000
	Nervous problems	–0.0222	0.009
	Skeletal system diseases	–0.0136	0.000
	Diabetes	–0.0156	0.000
Homecare	Skeletal system diseases	–0.894	0.000
	Diabetes	0.2216	0.002
Circulatory problems	Diabetes	0.365	0.003
Skeletal system diseases	Diabetes	1.187	0.000

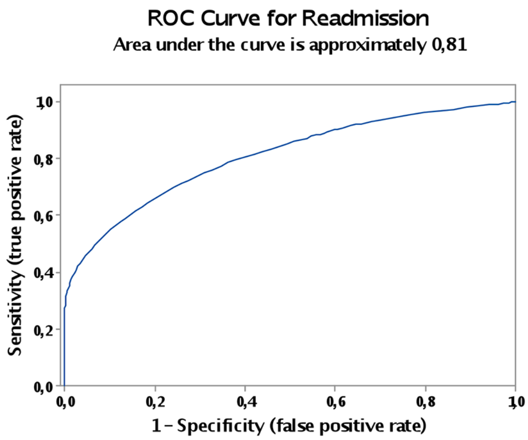

Figure 7. Receiving operating characteristic curve for the validation cohort.

Table 5. Classification results.

	Correct	Incorrect	Total
1	33305	12730	46035
0	31157	11805	42962
Total	64462	24535	88997

which evidences that a person having nervous disorders is more expected to return within 15 days if efficacious treatments (e.g., pharmacological interventions) are not applied. In this category, the most common diseases were: stroke, peripheral nervous disorders, central nervous system (CNS) neoplasms, non-hypertensive encephalopathy, and bacterial infections of the central nervous system. In this respect, it was found that deficiencies during post-hospital care are the leading cause. This is evidenced by an OR = 2.3220 (99% CI, 1.5536 - 3.4705), which denotes that a patient experiencing nervous system diseases is more than twice likely to request hospitalization services within 15 days after discharge compared to a person who does not suffer from this kind of disease. It is then crucial to ensure the participation of general physicians, neurologists, and families to effectively check the patients' clinical progress by implementing outpatient care programs, compliance with the prescribed medical regimen, collaborative care, and self-management.

Skeletal system diseases

"Skeletal System Diseases" (C = 0.55) was also found to positively contribute to the probability of readmission within 15 days after hospital discharge, which demonstrates that a patient suffering from skeletal abnormalities is more prone to be readmitted if prevention interventions are not implemented. Diseases enlisted in this category are arthritis, osteoporosis, and bone cancer. Another finding underpinning this statement is that the OR = 1.7109 (99% CI, 1.4327-2.0431) establishes that, for a person experiencing skeletal system illness, the probability of being readmitted is 1.7109 larger than the odds for a healthy person. On the other hand, four significant skeletal-diseases-related interactions were also detected in this study. These combinations include: AGE (p-value = 0.003; C = –0.0144), Number of Procedures (p-value = 0.001; C = –0.1907), Number of Diagnoses (p-value = 0; C = –0.1168) and Homecare (p-value = 0; –0.894). Concerning AGE*Skeletal System Diseases interaction, a research study established that elderly people lose bone mass due to lack of calcium, and therefore, corporate support, physical mobility, and protection of vital organs can be negatively affected [37]. Meanwhile, if a patient having skeletal system diseases is discharged to a homecare program, serious adverse events may be experienced due to the household-related hazards

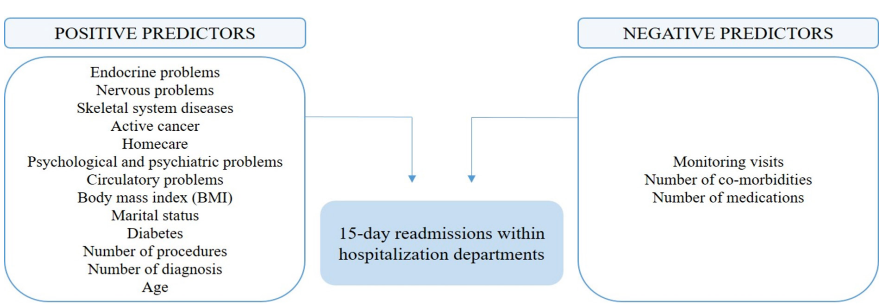

Figure 8. Summary of positive and negative predictors of 15-day readmissions.

associated with residential settings. It is then relevant to guarantee that diagnosis, inpatient/outpatient care, and homecare are multidisciplinary, focusing on identifying hazardous conditions and latent failures to design integral improvement strategies mitigating the risk of 15-day readmission.

Active cancer

Another significant predictor was "Active Cancer" (p-value = 0; C = 0.427), which denotes that an oncology patient is more prone to early return compared to a patient who does not suffer from this illness. Specifically, the odds ratio (OR = 1.3492, 99% CI, 1.1211; 1.5093) points out that the risk of 15-day readmission increases by 34.92% in this group of patients. The reported literature also provides valuable evidence on this aspect [38, 39]. Regarding the root causes of readmission in patients undergoing cancer treatments, some authors [39] established that hospitals mostly readmitted oncology patients with vomiting 36 hours after discharge, abdominal pain 48 hours post-discharge, and electrolyte disturbances. Concerning outpatient care strategies aiming to reduce readmissions, it is important to implement palliative care in early-stage and late-stage cancer. It is also useful to monitor the progress of these patients during the initial hospitalization to identify potential causes of readmissions and design effective and customized patient care plans.

Homecare

It was also identified that deficiencies in "Homecare" end up with new readmissions (C = 0.37) in a period even shorter than 15 days. In this regard, outpatient care should be strictly designed, implemented, and monitored to improve the patient recovery quality and subsequently diminish the number of new admissions. Despite the advantages of homecare services (e.g., autonomy and freedom for patients, lower infection rates), some disadvantages have to be tackled. For instance, patients often misunderstand homecare instructions, which results in a lack of adherence to medical treatment and the subsequent potential life-threatening complications. Additionally, it was found that homecare providers evidenced limited knowledge when teaching patients and families, evaluating their self-care ability, assessing patients' condition, and providing direct care. The problem is even sharper when considering that the risk of readmission can increase by 44.41% (99% CI, 32.61% - 57.25%) when there are medication errors, lack of treatment adherence, and inconsistent quality of care. Thus, when low-quality homecare programs are applied in the elderly, the readmission rate can be even higher (p-value = 0; C = –0.0038). Patients' age compromises the stability of the immune system. The extreme ages are factors of health instability. In the first few years, the immune system is still immature; in contrast, it becomes senescent in old age. Furthermore, if the above-mentioned failures occur in patients with co-morbidities, the risk of readmission can be also dramatically augmented (p-value = 0; C = –0.1705). It is hence relevant to correctly identify and analyze the patients' clinical background to minimize the risk of adverse events. This is especially important in diabetic patients, which can be readmitted if homecare agencies fail to assist them (p-value = 0.002; C = 0.2216). Moreover, it is essential to train homecare nurses, improve the communication among physicians, patients, nurses, and related relatives to monitor the emotional and physical condition of patients effectively as well as increase the quality of care.

Psychological and psychiatric problems

On the other hand, the presence of "Psychological And Psychiatric Problems" in patients previously hospitalized may result in earlier returns to these departments (C = 0.344). If these kinds of disorders are not properly addressed once patients with elevated depression scores leave the hospital, new visits can be expected. This is consistent with the reported literature [40, 41] where depression, schizophrenia, bipolar disorder, the use of psychoactive substances, and emotional disorders have been identified as the main causes of readmission within this category. The specific increased percentage for the readmission of these patients was calculated to be 44,30% (99% CI, 10.87% - 87.80%). The risk is even higher when psychiatric patients suffer from other clinical conditions (p-value = 0.009; C = –0.1321). In this regard, a study expressed that this association is very common in a clinical setting. Specifically, chronic lung conditions, hypertension, and hepatitis C virus were identified as the most contributing diseases in psychiatric patients [41]. Therefore, the combination of these conditions worsens patients' physical health and consequently leads to frequent readmissions. To this end, the participation of a multidisciplinary team and an effective communication flow among patients, their families, and hospital representative after discharge (including the prescription of pharmacological treatments, continuous patient monitoring, and the rigorous control of the home healthcare environment) seem to be the most effective strategy to reduce readmissions related to psychological and psychiatric disorders.

Circulatory problems

It was also detected that "Circulatory Problems" are also a significant 15-day readmission cause (C = 0.34). Therefore, if patients who suffer from these diseases are not included in effective prevention programs, overcrowding may be possible in both emergency and hospitalization departments. This finding is also consistent with the reported literature in this area [42]. Furthermore, it has been estimated that this condition makes the risk of readmission increase by 39.43% (99% CI, 22.66% - 58.49%) and should be hence assessed and highly monitored after hospital discharge. In this respect, some authors found that poor care quality during and after hospitalization stay in addition to patient characterization errors are the leading causes of readmissions related to circulatory diseases [42]. This is attributed mostly to patients, and their families lack sufficient knowledge about the changes related to pharmacological treatments, follow-up tests, and control appointments. Another aspect of concern is that high-risk patients do not have access to effective outpatient programs for disease control and prevention [42]. It is then necessary to create strategies focusing on planning hospital discharges where aspects like pharmacological treatments and continuous monitoring (within the 7 days after discharge) should be carefully considered to reduce the readmission and mortality rates. It is also suggested to develop outpatient healthcare networks integrating related medical staff to improve the communication flows and deploy education programs addressing the identified weaknesses.

Body Mass Index (BMI)

Apart from the above-mentioned findings, "BODY MASS INDEX (BMI)" was associated with 15-day readmission (C = 0.29) but in a lower grade. In particular, it was found that the likelihood of readmission augments by 33.43% (99% CI, 24.36%-43.16%) in obese people (BMI > 30 kg/m^2). Several studies confirm these important findings [43]. The increased body mass index is associated with hypertension, diabetes, and elevated cholesterol and triglycerides levels, while the risk of suffering from cardiac diseases is also meaningfully augmented. On the contrary, a low weight (BMI < 19.9 kg/m^2) also represents a contributing factor to 15-day readmission due to the hormonal balance, bone density, muscle mass, and stability of the circulatory system can be severely affected. This problem is even sharper in the elderly (p-value = 0) when considering that an increased BMI in people between the ages of 50 and 75, can decrease the life expectancy by 28% if suitable interventions are not deployed. Thus, patients should be taught to incorporate healthy habits to keep BMI under control: i) improve the eating habits (increase fruit and vegetable consumption) ii) do regular physical activity, iii) stop smoking, and iv) moderate alcohol consumption. This has to be complemented by the continuous monitoring of patients' weight to reduce the risk of readmission and improve quality of life in hospitalized patients.

Marital status

Another aspect of intervention is "MARITAL STATUS", which was significantly correlated with 15-day readmission (p-value = 0; C = 0.2866). In particular, it was estimated that the risk of readmission could augment by 32.82% (99% CI, 25.08% - 41.02%) in divorced and widowed patients. In fact, a study expressed that these patients are more expected to return early compared to those who are married [44]. This is since patients' home and social environments, after hospital discharge, affect patients' health conditions. In this sense, widowed and divorced people lack support during the recovery period, which ends up diminishing the effectiveness of pharmacological treatments and outpatient care. On the contrary, married patients count on emotional support from their families, which can also monitor the progress of their health status. On the other hand, significant interactions, including "Marital Status", were also detected. For instance, when combined with "AGE", the resulting p-value was equal to 0. In this respect, it was found that the risk of readmission is higher in elderly patients who live alone since they are more dependent on help in their daily living [44]. Additionally, when the elderly lose a spouse, they tend to have an increased risk of nutrition deficiencies, which augments the readmission risk . It was also noticed that the "Number of Diagnoses" interacts significantly with the marital condition (p-value = 0). This is underpinned by the fact that patients who live alone will need more home support to adhere to multiple drug treatments and physician recommendations effectively. Another aspect of interest is the combination of "Marital Status" and "Number of Procedures", which was also concluded to be statistically meaningful (p-value = 0.001). In this sense, the family can provide practical support by considering the range of limitations the patient could have both in the short and long term, the diet, medications, and follow-up appointments enlisted in the discharge lists. Furthermore, emotional support is vital for a person who is still suffering the after-effects of their injuries to avoid a long recovery or a permanent disability. Also, the interaction between "Marital Status", and "Number of Medications" has to be further studied (p-value = 0; C = 0.5010). Patients' families play an important role in improving adherence to multidrug regimens (polypharmacy) while reducing the likelihood of readmission. 15-readmission rates are also affected when particular interactions between "Marital Status" and "Number of Lab Procedures" occur (p-value = 0). Hence, it is essential to create multidisciplinary pre-emptive plans to stabilize widowed and divorced patients before readmission is required. Social discharge planners can be integrated into the outpatient settings to better define and coordinate the follow-up process so that patients' well-being can be ensured to alleviate the burden faced by these patients.

Besides the abovementioned factors, another critical patient characteristic in 15-day readmission is "Sex" (p-value = 0; C = 0.1646). According to the results, female patients have a higher risk of 15-day readmission compared to males. In effect, the odds ratio indicates that, for a woman, the probability of being readmitted is 1.1788 (99% CI, 1.1212 - 1.2392), larger than the odds for a man. This can be attributed to the fact that gonadal oestrogens are associated with metabolic syndromes and cardiovascular diseases. Similarly, several reports have concluded on the importance of sex as a classifying criterion for readmissions [45, 46]. In detail, it was established that women are more prone to readmission compare to men [45]. They also reported that women tend to experience a high level of stress after hospital discharge, which ends up increasing the readmission rates. Lack of suitable education and discharge planning has also been detected as a source of readmission in this population sector. On the other hand, significant correlations between "Sex" and the following factors were identified and should be well managed when developing preventive actions: "AGE" (p-value = 0.001), "Number of Procedures" (p-value = 0.002), "Number of Diagnoses" (p-value = 0), "Number of Medications" (p-value = 0) and "Number of Lab Procedures" (p-value = 0). In this sense, hospital discharge planning should be co-ordinately set amidst physicians, nurses, and support staff to fully characterize patient's outcome to determined potential risks. The subsequent monitoring plans and medical treatments can be effectively generated.

Minor positive contributors

Finally, other positive contributors were detected in this study although with a less strong association (1 < OR < 1.1) with 15-day revisits: "Diabetes" (OR = 1.0725; 99% CI, 1.0107 - 1.1382), "Number of Procedures" (OR = 1.0518; 99% CI, 1,0335 -1.0705), "Number of Diagnoses" (OR = 1.0508; 99% CI, 1.0372 - 1.0646), "AGE" (OR = 1.0189; 99% CI, 1.0175 - 1.0203). Yet, these predictors were concluded strongly correlated when combined with other factors and should be therefore further monitored to reduce the readmission.

Negative coefficients

In contrast, 3 factors were found to have negative coefficients. First, it was concluded that patients with "Monitoring Visits" (p-value = 0; C = – 0.7561) are less likely to be earlier readmitted in hospitalization than an unmonitored patient. The calculated odds ratio was 0.4743 (99% CI, 0.4446 - 0.5060), which points out that the probability of a new visit decreases by 52.57% when the patient is properly monitored and controlled by the discharging hospital. Also, a significant correlation between this factor and "AGE" (p-value = 0) was found. Hence, hospital discharge planning should be carefully designed considering the aggravating conditions of the elderly and the burden faced by their caretakers. The interaction, including "Number of Co-Morbidities" was also associated with this type of readmission (p-value = 0). Although substantial resources are required to address this problem, it is recommended for hospitals to rigorously intervene with improvement strategies to achieve increased patient satisfaction, avoid potential readmissions, and diminish cost overruns. These results were also found by governmental reports

[47] and other studies [48]. It is then remarkably important to count on the participation of related medical staff through periodical visits and follow-up calls in addition to assessing and monitoring the home and family environment of the patient so that preventable readmissions can be avoided. Another predictor with negative coefficient was "number Of medications" (p-value = 0; C = –0.0067). Yet, its odds ratio was close to 1 indicating a very slight affectation on readmission rates (OR = 0.9944, 99% CI, 0.9904 - 0.9984). On the other hand, Pearson, Hosmer-Lemeshow, and deviation chi-squared tests indicated sufficient evidence to claim that the logistic regression model fitted the data adequately (P-value > 0.01). The model's discrimination ability is excellent (Area under curve = 0.81) and is, therefore, a suitable and easy-to-apply method to categorize discharged patients according to their readmission risk. Depending on the risk, multivariate prevention plans can be introduced by healthcare decision-makers to reduce the readmission probability.

CONCLUSIONS

In the present research, the hospital readmissions problem was analyzed due to the importance of the topic. The importance of improving good practices in healthcare has motivated many interventions attempting to tackle this problem. In this research, a statistical model was designed to measure the likelihood of 15-day readmissions in hospitalization departments. Our model allows classifying patients into a risk category. In this way, prevention plans can be created for each patient to reduce the probability of an unplanned 15-day return. The model provides sufficient information to analysts who are interested in managing hospital readmissions problem. Also, it suggests that simple and accessible parameters are used to identify patients at high risk for hospital readmission.

In particular, the endocrine and nervous problems were found to significantly increase the 15-day probability readmission in hospitalization units; while, monitoring visits were concluded to cause the opposite effect. On a different tack, 45 two-term interactions were identified to contribute to the readmission problem, which evidences the need for bi-dimensional prevention strategies tackling this risk. Ultimately, the model discrimination was estimated to be 0.81 and is therefore considered excellent for prediction.

The aim of future research work will be two-fold. Firstly, future work should validate the outcomes proposed in this research and analyze any potential factors contributing to the current problem. It should then investigate the adoption of a "holistic" model to promote the highest level of integration among the care networks in Colombia. Of course, the proposed model and future research are scalable in other realities.

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