Risk Factors Associated with Hospital Unwarned Appointment Absenteeism: A logistic binary regression approach

Miguel Maia
Ana Borges
Mariana Carvalho*
8170246@estg.ipp.pt
aib@estg.ipp.pt
mrc@estg.ipp.pt
CIICESI, ESTG, Politécnico do Porto
Felgueiras, Portugal

ABSTRACT

One of the main problems faced by health institutions is the unwarned absenteeism of patients in medical appointments. Patients' no-shows, without prior notice, can result in loss of revenue for health centres and increasing waiting lines. Hence, there is a need to predict the non-attendance of patients to improve health institutions' management performance. In this paper, a brief literature review was carried out to understand which factors can be related to patients' absenteeism, and which forecasting methods are often applied to discover patterns in health datasets. As the logistic binary regression model has been proved to be effective on that matter, it was applied to a real hospital data set comprising information on 98.511 patients, with a corresponding 645.576 appointments, in a period between 2018 and 2020. Results indicate a significant effect on the chance of appointment attendance of patient age, patient gender, patient Marital Status, number of previous appointments, appointment month, precipitation levels, Lead time, and the number of previous no-show appointments.

CCS CONCEPTS

• **Computing methodologies → Modeling and simulation**.

KEYWORDS

No-show, hospital appointment, logistic binary regression

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1 INTRODUCTION

Patient absenteeism has become an alarming situation, not only nationally, but worldwide, becoming a chronic problem [13]. A vast number of patients miss their appointments, either for not being able to cancel in time or not being able to cancel the appointment at all. Since one of the primary goals of health services is the care of patients to solve individual and collective health problems, when this service is not carried out, there is a loss of opportunity to offer help to another patient who needs care, and a financial and marketing loss. The non-attendance of patients causes a huge waste of health resources and the lack of any type of communication obstructs the rescheduling or insertion of other patients in the opening hours to improve the efficiency of the institution [3],[4] Therefore, the non-attendance patients could result in wasting billions of dollars in inactive, overtime and waiting time that involve hospitals and patients [1]. For reasons related to the previously defined implications, there is a need for a solution to address the non-attendance patient rates and try to understand why they occur. Therefore, in this paper, the authors aim at understanding the reasons associated with the patients missing their scheduled appointments and predict the no-show patients of a hospital located in the North of Portugal. The contributions of this paper are a) the improvement of the efficiency of the Hospital by helping to understand the profile of its patients and helping understand the factors that lead them to miss their appointments, and b) test different methods that lead the Hospital to understand the identified problem. This paper is organized as follows: Section 2 presents a review of literature, allowing us to understand which is the impact of non-attendance patients and the main factors that can impact this situation. Also, in this section, the authors analyze which are the models used in non-attendance patient studies. In section 3, the authors present the methodology followed in this study and section 4 the application of the model and interpretation of results. And finally, section 5 concludes the paper and discusses some future work.

2 LITERATURE REVIEW

In this section, the author's present a brief literature review on patients absenteeism in hospital appointments. This is a widely discussed subject, since, with the evolution of technologies and the amount of information generated, there is a need to improve the hospital's or health centres' management system and avoid wasting resources. According to [3],[9], when patients miss their medical appointments, it can have harmful effects in several aspects, namely, in the patient, in the health system and public health. [9] also, reinforce that for at-risk and disadvantaged populations, the delay in the provision of care is a threat to their health care. For [3], the concept of absenteeism in medical consultations should be highlighted, since it leads directly to the waste of structural, financial resources and social costs. Productivity indicators related to employees, equipment and office are greatly affected as well as costs that increase due to the idleness of available resources. One of the medium-term effects of absenteeism is undoubtedly the intensification of queues for procedures. Several authors study the factors that could influence the non-attendance of patients, namely [12], [8] These authors identify several clinical factors, for example, the difficulty of scheduling a medical appointment or even communication between the clinic and the patients, leading to an unstable relationship between them, long waiting times between the requisition and confirmation of the appointment and the appointment itself. Regarding demographic factors, these authors point to other causes such as: being female; residing in a lower socioeconomic zone; and having fewer educational qualifications. The authors perform the prediction analysis using a multiple logistic regression model. Other authors were able to predict the non-attendance of patients to scheduled appointments, resorting to machine learning algorithms: using logistic regression methods [4], [11] neural networks [11] and the Naive Bayes classifier [11]. The authors use in their study a database is composed of several independent variables: type of clinic, waiting time, age, sex, marital status, race, whether they have a cell phone number, use of insurance and whether they are a smoker or non-smoker. [5] manages to gather several factors that could lead to patient non-attendance. These factors are divided into: a) Patient demographics: age, gender, language, race/ethnicity, employment status, marital status, economic status, educational completion, insurance/payment, postal code, distance/transport, religion and access to mobile phone; b) Medical history: type of clinic, speciality, previous visits, service provider, referral source, diagnosis, duration of diagnosis, first visit/follow-up visit; c) Scheduling/appointment details: month, day of the week, visiting hours, vacation indicator, one-day visit, weather, season, visit interval, lead time, waiting time, scheduling mode; d) Patient behaviour: past no-shows, past cancellations, last appointment status, satisfaction and late visit. To perform the model, the authors used the logistic regression model, decision tree, neural networks and Markov and Bayesians. Years later, some authors used the decision tree model, which is seen as the most widely used model after regression models. This model was also widely used in the literature from the 1980s onwards [5]. With this review, the authors feel confident moving forward and analyzing which are the factors that could impact the non-show patients in this study. To perform the study and discover which are the factors, the authors decide to resort to the logistic binomial regression model, since it is one of the most used models in similar studies.

3 METHODOLOGY

To infer the factors related to the probability of patients' no-shows to their scheduled appointments, in a hospital located in the north of Portugal, patient information was collected from the hospital's electronic platform. Additionally, exogenous information on weather conditions and calendars was also collected. In subsection Data a brief is presented as a clarification on the variables collected and tested. To test the effect of each variable in the probability of appointment attendance, the logistic binary regression model was applied, using a dummy dependent variable the attend variable that takes the value 0 in no-show situations, and 1 otherwise. As mentioned in the previous section, this type of model has been successfully applied in the analysis of this nature. As a first exploratory analysis, multiple univariate logistic binary models were adjusted for each variable to understand the individual effect on the chance of attending the appointment. Next, a multivariate logistic binary model was fitted considering only the variables with a significant effect on the chance of attending the appointment. All data was pre-processed using Python and analyzed using IBM SPSS software version 28.

3.1 Data

Data were collected from informatic records on 98.511 patients with a corresponding 645.576 appointments, at a hospital located in the north of Portugal, in a period between 2018 and 2020. The final dataset comprises information at the patients' level, at the appointment level. To enrich the dataset, the authors decide to include data like weather conditions and calendar information, since it proved to be related to no-show prediction in the literature. The weather data was fetched using the Weather API. Table 1 summarizes the variables that constitute the dataset. And Table 3, in the appendix, presents brief descriptive statistics of the analyzed variables. Succinctly, the no-show average rate per patient is 0,97 appointments/patient, however, this rate value ranges from 0 (patients that never missed an appointment) to 1186 appointments/patient (a patient that missed 1186 appointments). Patients ages range between 0 and 116 years, with an average of 41,06 years. More than half (55,3%) are female patients. And, for the patients with information on marital status, the majority is Married or single (1875 and 2344 patients, respectively).

Table 1: Variables included in the analysis

Variable	Description
Attendance	Dummy variable: 0 if the patient missed appointment, 1 if patient attended the appointment
Age	Patient age in years
Marital status	Categories: Widowed, Married, Divorced, Single, Cohabiting, Other.
Distance	Distance in km from residence to hospital
Speciality	Type of hospital speciality: 50 in total.
Previous Appointments	Number of appointments of the patients before the appointment analyzed.
First Appointment	1 if it is the first appointment of the patient, 0 otherwise
Month	Month on which the appointment occurred
Weekday	Day of the week on which the appointment occurred
Min Temp	Minimum temperature of the appointment day
Max Temp	Minimum temperature of the appointment day
Mean Temp	Mean temperature of the appointment day
Humidity	Humidity average level on the appointment day
Precipitation	Precipitation average level on the appointment day
Wind Speed	Wind Speed mean on the appointment day
Lead time	Time, in days, interval between the schedule of the appointment day and the appointment day.
No show	Number of previous no-shows.
Season	Season of the year: Winter, Autumn, Spring and Summer.

3.2 Model

The logistic binomial regression model has been widely applied in patients' no-show (e.g, [13], [9], [12], [8], [11]). This model is a particular case of the general linear models (GLM) that predicts the probability of occurrence of an event (in our case the patient attending a consultation), by fitting numerical or categorical predictor variables to a logit function [6]:

$$logit(p) = ln(\frac{p}{1-p}) = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k \quad (1)$$

Where p and *1-p* are the corresponding odds of attending an appointment and not attending the appointment, respectively, given that a set of explanatory variables and unknown regression coefficients $\beta_j, (0 < p < k)$, to be estimated through maximum likelihood methods.

The logistic function can be written as:

$$p = \frac{1}{1 + exp(-(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k))} \quad (2)$$

Or one can write the model in terms of odds as:

$$\frac{p}{1-p} = 1 + exp(-(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k)) \quad (3)$$

Note that, the logistic regression results reports on Odds Ratio (OR) and not on probabilities (Risks), directly. The higher the OR, the greater the chance of the outcome occurring (attending the appointment) in a given group compared to the other and, consequently, the greater the risk. For the multivariate model, the Conditional Backward Elimination procedure, implemented in SPSS, was used for the selection of the variables entering the model. This procedure removes the non-significant variables by a test based on the probability of the likelihood-ratio statistic based on conditional parameter estimates. To test the model goodness-of-fit, the Hosmer-Lemeshow statistics [7] was calculated with the null hypothesis that the observed and expected proportions are the same across all doses. Rejecting the null hypothesis indicates that the model does not adequately fit the data.

4 RESULTS

The univariate binary logistic models (Table 4 in Appendix) of the large set of tested variables, chosen with literature support, allow us to understand that variables at patient level such as patient age, sex, marital status, and distance from home to hospital presented a statistically significant effect on the probability of attending a consultation. Also, the consult speciality type presents a significant effect on the chance of attending the appointment. The number of previous appointments is related to a higher risk of a no-show. Regarding exogenous variables, it was found a significant effect of the month, the weekday, the precipitation mean level, the wind speed mean level and the season on the chance of attending the appointment. Furthermore, variables related to the patient behaviour towards the risk, such as lead time and the number of previous no-shows also present as risk factors on the chance of attending. Higher values of lead time and previous no-shows lower the chances of attending the appointment.

As previously mentioned, the multivariate logistic model 2 was fitted considering all the significant variables obtained in the univariate models[1]. However, the Conditional Backward Elimination procedure discarded some variables, resulting in a model with significant variables such as patient age, patient gender, patient Marital Status, number of previous appointments, appointment month, precipitation levels, Lead time, and the number of previous no-show appointments.

[1] To control for possible multicollinearity problems, the VIFs were calculated for all the variables on the saturated model. As the corresponding VIFs values, for all variables were around 1, the problem of multicollinearity was rejected. Also, the Specialty variable was not included in the multivariate model due to its large number of categories and the suspicious estimates obtained for Anatomic Pathology and Immunology.

From the results, as a first attempt at profiling the patients one could say that older patients tend to have a higher chance of attending the consultation (OR=1,009), masculine patients are the ones who have a lower risk of not attending the consultation (OR=1,244), and cohabiting situation patients (OR=0,621) tend to have a lower chance of attending than widowed patients. Contrariwise, although with marginal effect at a 5% level of significance, patients in undescribed (other) marital status (OR=1,151) present a higher chance of attending than widowed patients. Regarding the patient's behaviour towards the risk, Lead time, i.e. the time between the appointment schedule and the appointment date, is significantly related to the odds of attending the consultation in the way that the longer the time between the scheduling and the appointment the higher the risk of a no-show (OR=0,9995). Also, in this matter, the higher the number of previous no-shows the higher the chance of no-show (OR=0,965). Also, the chance of attending the appointment (OR=1,009) increases with the increase of the number of previous appointments. Concerning exogenous variables, only the mean levels of precipitation showed a significant effect on the odds of attending, where higher levels of precipitation increase the chance of not attending the appointment (OR=0,9991).

The logistic multivariate model was statistically significant (omnibus test of model coefficients: $\chi^2(48) = 824,225$,$p - value < 0,001$). However, the low value of the R^2 Cox & Snell (0,053) and of the R^2 Nagelkerke (0,080) obtained point to the possibility that the variables explain a low variation of the dependent variable (between 5,3% and 8%). These advocates for the necessity of furthermore exploring factors related to the probability of no-show. Moreover, results significant for the Hosmer-Lemeshow, $\chi^2(8) = 31,777$, $p - value < 0,001$, questioning the validity of the model. However, as some authors point out when the Hosmer-Lemeshow goodness-of-fit test is performed with several covariate patterns lower than the number of subjects (as in this case) its result may be inaccurate [2]. As [10] discuss, the Hosmer-Lemeshow test is sensitive to sample size, and a significant Hosmer-Lemeshow test does not necessarily mean that a predictive model is not useful or suspect.

5 CONCLUSION

In this paper, the authors present a study on no-show patients using a logistic regression model to understand which factors have an impact on the patients' appointments absenteeism. First, an overview of studies on this matter was conducted to allow us to understand which factors are usually considered in the literature, and the models proved to be effective in studies of this nature. The logistic binary regression model has proven to be capable of predicting the chance of attending versus not attending hospital consultations [4], [11].

As so, to infer the factors related to the probability of patients' appointment no-shows, data from a hospital located in the north of Portugal was collected and analyzed. The validity of the logistic model on the prediction of the probability of appointment attendance, regarding a set of explanatory variables, was tested.

Results point out a multivariate significant effect of patients age, sex, marital status, number of previous appointments, lead time, number of previous no-shows, mean levels of precipitation and appointment month, on the probability of appointment attendance. However, some problems should be pointed out. The fact that the model was unable to estimate the effect of some consultation specialities suggests the need of refining the analysis considering, in the future, one model per speciality. Also, the goodness-of-fit statistics obtained and the low explained variability compromise the validity of the prediction model, pointing to the need to test new models and new variables. In fact, for future work, we intend to use other mentioned machine learning models (in section 2) such as a decision tree algorithm, naïve Bayes or neural networks and hopefully compare results. Also, we intend to perform an unsupervised learning algorithm to obtain a descriptive analysis of the data and possibly perform patient profiling of the hospital.

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Table 2: Estimates obtained for the final multivariate model

Variable	OR	CI95%	p-value
Age	1,009	[1,006;1012]	<0.001
Sex (Reference: feminine)			
Masculine	1,244	[1,145;1,352]	<0.001
Marital Status (Reference: Widowed)			
Married	0,97	[0,765;1,231]	0,805
Divorced	1,208	[0,263;5,554]	0,808
Other	1,151	[0,999;1,327]	0,052
Single	1,111	[0,655;1,885]	0,697
Cohabiting	0,621	[0,489;0,789]	<,001
Previous Appointments	1,011	[1,099;1,013]	<,001
Month (reference: January)			
February	1,148	[0,942;1,401]	0,172
March	0,637	[0,531;0,763]	<,001
April	0,676	[0,554;0,824]	<,001
May	1,008	[0,824;1,231]	0,942
June	1,072	[0,879;1,308]	0,49
July	0,945	[0,781;1,144]	0,561
August	1,228	[0,995;1,515]	0,055
September	0,839	[0,697;1,01]	0,064
October	0,877	[0,728;1,058]	0,17
November	0,849	[0,714;1,01]	0,064
December	0,994	[0,816;1,211]	0,954
Precipitation	0,999144	[0,9998615;0,999674]	0,002
Lead Time	0,9995	[0,99945;0,99954]	<,001
No Show	0,965	[0,959;0,971]	<,001

A APPENDICES

A.1 Descriptive Statistics Tables

A.2 Model Fitting Tables

Table 3: Descriptive Statistics Tables

Panel A - Descriptive characteristics of patients					**Panel B - Descriptive characteristics of consultations**				
	Mean	SD	Min	Max		Mean	SD	Min	Max
Age	41,06	22,59	0	116	**Precicipation**	5,21	11,55	0	97,36
Distance	19,077	185,74	2,58	10772,48	**Wind speed**	19,77	6,57	6,3	55,8
Appointments Attended	4,59	10,3	0	639	**Previous Appointments**	13,28	27,092	0	639
Appointments not attended	0,97	5,69	0	1186	**Lead Time**	367,85	595,03	12,15	35100,78
	N	%				N	%		
Sex					**Month**				
Feminine	52379	55,3			January	50004	0,085		
Masculine	42327	44,7			February	48507	0,083		
Marital status					March	43984	0,075		
Married	1875	2			April	32423	0,055		
Divorced	98	0,1			May	44208	0,075		
Other	9	0,009			June	44182	0,075		
Single	2344	2,5			July	52419	0,089		
Cohabiting	25	0,026			August	45593	0,078		
Widower	100	0,1			September	50514	0,086		
					October	55613	0,095		
					November	75240	0,128		
					December	44998	0,077		
					Day of the week				
					Monday	52401	0,089		
					Tuesday	925	0,002		
					Wednesday	101589	0,173		
					Thursday	112874	0,192		
					Friday	106534	0,181		
					Saturday	106261	0,181		
					Sunday	107101	0,182		
					Season				
					Autumn	151720	0,258		
					Spring	124914	0,213		
					Summer	140809	0,24		
					Winter	170242	0,29		

Table 4: Estimates obtained for univariate models

Variable	OR	IC95%	p-value
Age	1,005	[1,005;1,006]	<0.001
Sex (Reference: feminine)			
Masculine	0,809	[0,798;0,819]	<0.001
Marital Status (Reference: Widowed)			
Married	1,024	[0,904;1,160]	0,71
Divorced	0,683	[0,582;0,803]	<0,001
Other	0,896	[0,578;1,388]	0,622
Single	0,866	[0,764;0,981]	0,024
Cohabiting	0,803	[0,638;1,009]	0,06
Distance	0,999793	[0,999776;0,999810]	<0,001
Previous Appointments	0,998029	[0,997821;0,998236]	<0.001
First Appointment (reference: No)			
Yes	1,011	[0,972;1,051]	0.583
Month (reference: January)			
February	1,049	[1,017;1,082]	0,003
March	0,65	[0,630;0,670]	<0.001
April	0,739	[0,714;0,763]	<0.001
May	1,013	[0,982;1,046]	0,41
June	0,902	[0,875;0,931]	<0.001
July	0,945	[0,916;0,973]	<0.001
August	1,003	[0,972;1,035]	0,869
September	0,908	[0,881;0,936]	<0.001
October	0,941	[0,914;0,970]	<0.001
November	0,932	[0,906;0,958]	<0.001
December	0,936	[0,907;0,966]	<0.001
Weekday (reference: Sunday)			
Monday	0,675	[0,585;0,780]	<0.001
Tuesday	0,995	[0,970;1,021]	0,71
Wednesday	0,966	[0,942;0,990]	0,007
Thursday	1,005	[0,980;1,031]	0,686
Friday	1,044	[1,017;1,071]	<0.001
Saturday	0,949	[0,925;0,973]	<0.001
Min Temp	1,001	[0,999;1,002]	0,301
Max Temp	1,001	[0,999;1,002]	0,406
Mean Temp	1,001	[0,999;1,002]	0,44
Humidity	0,999973	[0,999460;1,000487]	0,918691
Precipitation	0,999144	[0,9998615;0,999674]	0,002
Wind Speed	1,002	[1,001;1,003]	<0.001
Lead Time	0,999294	[0,999283;0,999305]	0
No Show	0,984	[0,983;0,984]	0
Season (reference: Winter)			
Autumn	0,995	[0,978;1,012]	0,566
Spring	0,84	[0,825;0,855]	<0.001
Summer	0,999	[0,982;1,017]	0,923

Variable	OR	IC95%	p-value
Specialty (reference: Allergology)			
Anatomic Pathology	775891143,2	[0;.]	0,999
Anaesthesiology	3,002	[2,192;4,111]	<,001
Cardiology	2,229	[2,053;2,42]	<,001
Cardiology, Paediatric	3,519	[2,913;4,251]	<,001
Cardiothoracic Surgery	0,487	[0,345;0,689]	<,001
Aesthetic Reconstructive Surgery	1,508	[1,345;1,691]	<,001
General Surgery	2,491	[2,27;2,735]	<,001
Maxillofacial Surgery	1,73	[1,308;2,289]	<,001
Pediatric Surgery	1,476	[1,209;1,802]	<,001
Aesthetic and Reconstructive Plastic Surgery	1,596	[1,329;1,916]	<,001
Vascular Surgery	1,184	[1,069;1,311]	0,001
Dermatology	1,483	[1,361;1,616]	<,001
Endocrinology	0,923	[0,836;1,017]	0,107
Nursing	3,184	[2,879;3,522]	<,001
Gastroenterology	1,197	[1,075;1,334]	0,001
Genetics	0,48	[0,03;7,687]	0,604
Gynecology / Obstetrics	1,206	[1,111;1,31]	<,001
Hematology	1,612	[1,325;1,962]	<,001
Imaging	2,187	[2,02;2,368]	<,001
Immunohemotherapy	4,216	[3,067;5,794]	<,001
Immunology	775891143,2	[0;.]	1
Infectious Diseases	0,874	[0,649;1,177]	0,375
Dental Medicine	1,381	[1,273;1,497]	<,001
Pain Medicine	1,375	[1,066;1,775]	0,014
Aesthetic Medicine	0,86	[0,71;1,041]	0,122
Physical Medicine and Rehabilitation	1,127	[1,041;1,22]	0,003
General and Family Medicine	2,23	[2,041;2,437]	<,001
Internal Medicine	1,121	[1,021;1,23]	0,017
Neurosurgery	1,5	[1,32;1,704]	<,001
Neurophysiology	1,806	[1,582;2,062]	<,001
Neurology	1,673	[1,514;1,85]	<,001
Neuropediatrics	0,891	[0,648;1,225]	0,477
Nutrition	0,844	[0,685;1,04]	0,112
Nutritionism	0,699	[0,618;0,791]	<,001
Ophthalmology	2,116	[1,949;2,298]	<,001
Oncology	3,008	[2,447;3,697]	<,001
Orthopaedics	2,486	[2,289;2,701]	<,001
Otorhinolaryngology	2,05	[1,884;2,23]	<,001
Clinical Pathology	2,586	[2,377;2,814]	<,001
Pediatrics	1,02	[0,935;1,113]	0,655
Child psychiatry	0,874	[0,75;1,019]	0,086
Pulmonology	1,738	[1,585;1,905]	<,001
Podiatry	1,39	[1,176;1,643]	<,001
Psychology	1,209	[1,097;1,332]	<,001
Psychiatry	1,115	[1,022;1,216]	0,015
Rheumatology	1,375	[1,185;1,596]	<,001
Nursing service	4,148	[3,8;4,527]	<,001
Speech Therapy	1,481	[1,323;1,657]	<,001
Urology	1,651	[1,514;1,8]	<,001