Obesity Surgery (2019) 29:40–47
https://doi.org/10.1007/s11695-018-3480-9

ORIGINAL CONTRIBUTIONS

Predicting Patient No-show Behavior: a Study in a Bariatric Clinic

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Published online: 12 September 2018
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Abstract

Purpose No-shows of patients to their scheduled appointments have a significant impact on healthcare systems, including lower clinical efficiency and higher costs. The purpose of this study was to investigate the factors associated with patient no-shows in a bariatric surgery clinic.

Materials and Methods We performed a retrospective study of 13,230 records for 2660 patients in a clinic located in Rio de Janeiro, Brazil, over a 17-month period (January 2015–May 2016). Logistic regression analyses were conducted to explore and model the influence of certain variables on no-show rates. This work also developed a predictive model stratified for each medical specialty.

Results The overall proportion of no-shows was 21.9%. According to multiple logistic regression, there is a significant association between the patient no-shows and eight variables examined. This association revealed a pattern in the increase of patient no-shows: appointment in the later hours of the day, appointments not in the summer months, post-surgery appointment, high lead time, higher no-show history, fewer numbers of previous appointments, home address 20 to 50 km away from the clinic, or scheduled for another specialty other than a bariatric surgeon. Age group, forms of payment, gender, and weekday were not significant predictors. Predictive models were developed with an accuracy of 71%.

Conclusion Understanding the characteristics of patient no-shows allows making improvements in management practice, and the predictive models can be incorporated into the clinic dynamic scheduling system, allowing the use of a new appointment policy that takes into account each patient's no-show probability.

Keywords No-shows · Bariatric clinic · Appointment · Healthcare · Obesity

Introduction

No-show appointments (also commonly referred to missed appointments) are a problem for all health professions, significantly impacting revenue, cost, and use of resources [1, 2]. No-shows decrease the provider's productivity and efficiency, increase healthcare costs and limits the health clinic's effective capacity [3, 4]. Negative effects are also felt by patients who keep their appointments, such as dissatisfaction with long lead time and perception of the overall decrease in service quality [2, 5].

The literature indicates that patient no-shows do not happen randomly, and several studies have identified the need to

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s11695-018-3480-9) contains supplementary material, which is available to authorized users.

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statistically analyze the factors that influence its behavior in order to improve healthcare processes and minimize the effects of missed appointments. It is believed that the risks of future no-shows may be predicted and the contributing factors can be used to estimate this risk [4]. These factors can include patient socio-demographic data, clinical characteristics, appointment information, features of the environment, and/or features of the health professional [6], such as age, gender, race, socioeconomic status, marital status, lead time, prior no-show history, date and time of appointment, patient's symptoms, type of appointment, form of payment, distance to the clinic, among others.

Using the findings of the different effects and relationships between patient behavior and non-attendance rates for no-show prediction [2, 4, 7, 8], statistical models can be developed to simulate a dynamic scheduling system that considers each patient's no-show probability. Several works have proposed interventions to mitigate the negative effects of missed appointments, such as changes in the appointment-making policy, including overbooking [9–11], appointment reminders [5], best management practices, among others.

The literature about appointments in bariatric surgery has focused on analyzing adherence at post-surgery follow-up appointments [12–14]. Some studies have shown that attendance at follow-up appointments is associated with improved weight loss outcomes [12, 15, 16] and greater resolution of obesity-related medical comorbidities [14], by treating the non-attendance as an explanatory variable.

In this paper, we do not investigate appointments from the point-of-view of treatment success, but focus on the potential inefficiency of the clinic and its medical professionals due to patients missing their appointments (no-shows). Therefore, the focus of this study is to discuss which demographic factors and scheduling information influence patient no-shows in a Brazilian bariatric surgery clinic, considering the patient's previous no-show history. The aim is to develop predictive models and validate them, in order to be able to know each patient's no-show probability and draw a profile of no-show appointments. Each factor is also analyzed separately for each healthcare specialty. Knowing the patients who are most likely to miss an appointment can guide the clinic towards better orientation and care.

To the best of our knowledge, there are no publications about the factors based on scheduling information that influence no-show behavior at bariatric surgery clinics, nor an analysis of all types of appointments (before and after surgery) and medical specialties.

Materials and Methods

This study was conducted in a bariatric surgery clinic located in Rio de Janeiro, Brazil. The clinic has a healthcare team with different specialties (bariatric surgeon, psychologist, nutritionist, general practitioner, and endocrinologist), all focused only on the treatment of obesity. The study included only outpatient appointments, i.e., patient care in the clinic before and after surgery, not including hospital procedures or surgery scheduling.

The patients should be attended by these providers throughout their treatment, before and after surgery. Figure 1 shows the typical flowchart of the clinic and the time interval in which each patient should be attended by providers. However, unfortunately, this does not always happen because some patients give up treatment and miss their medical appointments.

The obtained dataset contains information on 2660 patients, rendering 13,230 appointments over a 17-month period (January 2015–May 2016). Of these records, we will not consider the first appointments of each patient (2660 records) for statistical analysis. This will allow us to have at least one appointment history for all patients considered. We performed the analysis using data that contained no information that could identify patients. All data had been anonymized and aggregated before being provided to us for analysis.

The outcome measure, no-show, was the failure of a patient to attend his/her appointment without canceling at least 48 hours before the appointment time. The unit of analysis is the appointment record, not the patient.

Three major groups of no-show factors were identified based on their availability in the clinic's electronic record system and through literature review [17]: (1) appointment characteristics, such as lead time (time interval between the date when the appointment is registered in the clinic's scheduling system and the actual appointment date), type of appointment, appointment month, weekday and time, form of payment (self-pay or health insurance), prior no-show history (existence of previously missed appointments by the patient), and number of previous appointments; (2) patient demographic data, including age and gender; and (3) other characteristics, such as healthcare specialty and distance between the clinic and the patient's home.

The appointment data points were randomly divided into development and validation cohorts (containing 70% and 30% of the data, respectively). A simple logistic regression model was built to investigate which variables influenced the no-show rate, one at a time. Variables with a p value less than $\alpha = 0.25$ were then considered as candidates for inclusion [18] in the multiple logistic regression, in which the significance level of $\alpha = 0.05$ was used to select the statistically significant variables. Then, we evaluated the performance of our final model. From this model, we can estimate the no-show probability for each individual and the profile of no-show patients. The data were also stratified by specialty, and the logistic regression analysis was repeated to observe possible differences across them. In addition, we analyzed statistically the

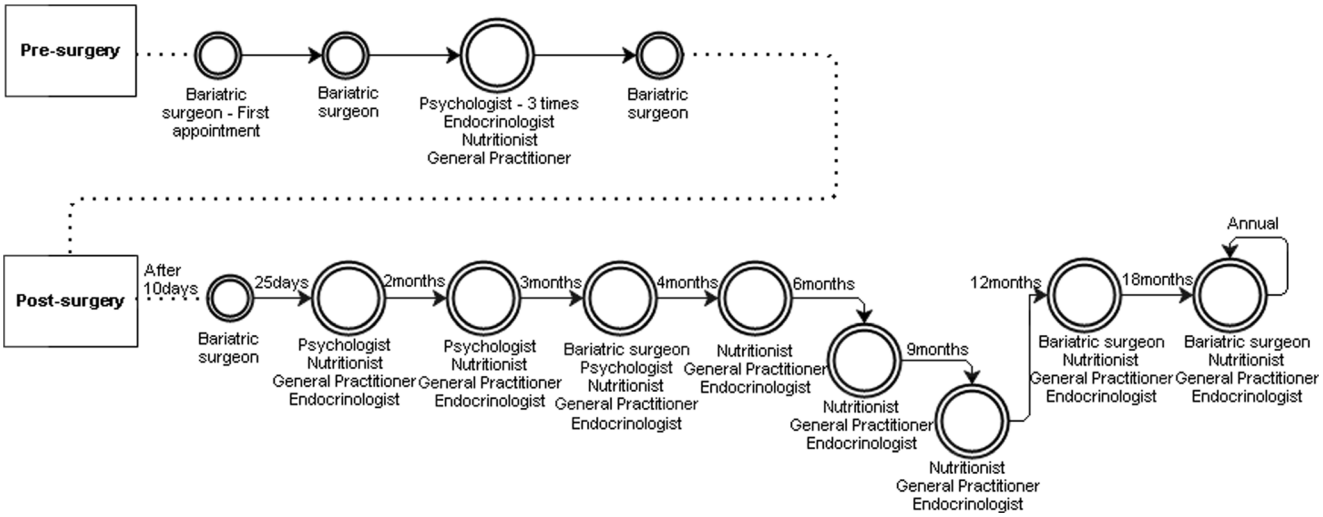

Fig. 1 Patient flow before and after surgery, related to the corresponding specialists

relationship between appointment type (pre- and post-surgery) and the other variables.

Data were extracted using the Standard Query Language (SQL) and were analyzed using the R software version 3.4.0.

Results

From the 13,230 appointments included in the study, there were 2897 missed and 10,333 attended appointments. So, the overall proportion of no-shows at the bariatric surgery clinic was 21.9%. Including all specialties, the maximal number of appointment per patient was 50, and the specialty "bariatric surgeon" was the one that had more appointments in the clinic (36.5% of the appointments).

Figure 2 presents the number of appointments and no-show rate before and after surgery for bariatric surgeons and other specialties. We can see that the missed appointments with the bariatric surgeons were higher in pre-surgery than in post-surgery cases. This happens because there are a large number of missed first appointments (Table 1), and these appointments are normally scheduled for bariatric surgeons. Conversely, after surgery, the patients tend to miss more of their follow-up appointments with the other specialties, discontinuing the treatment.

The mean patient age was 40 years old (ranging from 14 to 91), and the records reported that women were more likely to miss their appointments than men. Patients with private health insurance were more likely to miss their appointments than those responsible for paying their own medical expenses.

During the study period, 709 bariatric surgeries were performed, of which 95% of the patients underwent the "bypass" technique and 5% to the "sleeve" technique. Regarding the Body Mass Index (BMI) of the 2660 patients, about 18% had BMI values between 35 and 40, 56% between values 40 and 50, 21% between values 50 and 60, and 5% above of 60.

Table 1 shows the descriptive characteristics of the study population.

As previously stated, to allow us to have appointment history for all patients, we will not consider the first appointments of each patient in our statistical analysis. So, only 10,570 of the records were used for performing our statistical model. Through univariate analysis of those 10,570 records, we found 11 statistically significant variables ($p < 0.25$), which we included in the multiple analysis. The form of payment did not present statistical difference between the two groups.

From a multiple logistic regression, we identified that specialty, lead time, the hour of the day, previous no-show history, number of previous appointments, type of appointment, distance, and month were significantly associated with no-shows at a significance level of $\alpha = 0.05$.

Table 2 presents the results regarding both univariate and multiple analysis, including coefficients, ORs, OR (with 95% confidence interval), and p values for each independent variable. The reference level for each category is indicated in parentheses for each variable. In this case, OR > 1 predicts a lower likelihood of showing up for an appointment when compared to the reference level, whereas OR < 1 predicts a greater likelihood of showing up for an appointment.

Regarding the reduced multiple model, one can see that patients scheduled for a bariatric surgeon are more likely to attend their follow-up appointments. No-shows are 2.15 times more likely for patients scheduled between 4:31 pm and 6:30 pm than from 08:30 am to 10:30 am. However, patients scheduled between 10:30 am and 4:30 pm have a greater likelihood of showing up for an appointment than those scheduled before 10:30 am. Appointments in the months "Dec-Jan-Feb" are more likely to be attended. Additionally, patients with greater previous no-show history (≥ 50%) and fewer

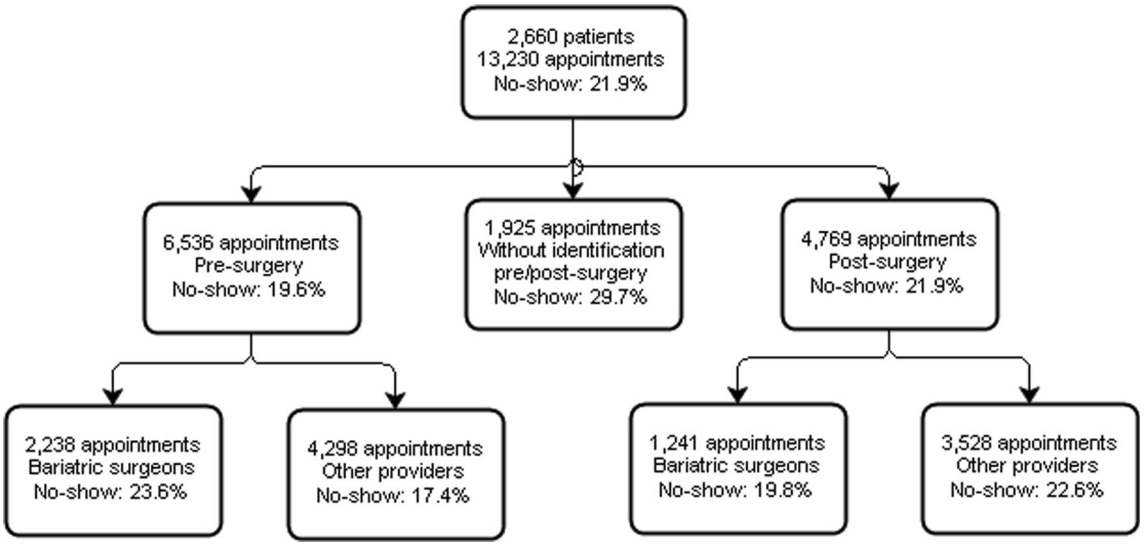

Fig. 2 Flow chart of the number of appointments and no-show rates before and after surgery for bariatric surgeons and other specialties

numbers of previous appointments (1 or 2) were more likely to miss an appointment. The post-surgery appointments have the greatest no-show rate (OR = 1.58). Scheduled appointments with up to 1-week lead time have the lowest no-show rate, and patients who live 20 to 50 km away from the clinic are the most likely not to attend. Age group, gender, and weekday were not significant predictors.

Our analysis revealed a pattern in the increase of patient no-shows: appointment in the later hours of the day, appointments not in the summer months, post-surgery appointment, high lead time, higher no-show history, fewer numbers of previous appointments (1 or 2), home address 20 to 50 km away from the clinic, or scheduled for another specialty other than a bariatric surgeon.

Using a cut-off of $p = 0.20$, the model had a sensitivity of 0.55, a specificity of 0.75, and an accuracy of 0.71 (95% CI, 0.69–0.73). In this case, the sensitivity and specificity are the percentages of "true no-show" and "true show", respectively.

The Supplementary Material I describes the statistical method used step by step and shows a practical application of the predictive no-show model.

In the logistic model, we found that the provider specialty was significantly associated with no-show. Therefore, to refine the analysis, we performed a stratified analysis by medical specialty. The medical team of the clinic attends the patients throughout their treatment according to Fig. 1.

The methods used in this section were the same as the previous analysis. The results can be seen in the Supplementary Material II.

Previous no-show history was the only factor that remained associated with failed appointments across all specialties. The greater the previous no-show history, the more likely it is for a patient to miss an appointment. The specialties most affected by the previous no-show history are psychology and nutrition. For example, patients who missed more than 50% of their prior clinic appointments (including all providers) are 14.65 times more likely to miss the next appointment with the psychiatrist and 8.42 times with the nutritionist when compared to patients with less than 10% of the prior no-show.

The type of appointment was significant for all specialties except bariatric surgeon. The post-surgical appointments have greater no-show rate than pre-surgical, mainly for the general practitioner and psychologist.

The other significant variables for each specialty were the following: lead time (bariatric surgeon and endocrinologist), appointment time (bariatric surgeon and psychologist), number of previous appointments (psychologist and nutritionist), weekday (nutritionist and general practitioner), distance (bariatric surgeon), and month (bariatric surgeon and nutritionist).

Patients are more likely not to attend when they have fewer prior appointments in the clinic. Fewer than 8 days from scheduling to the appointment was associated with the lowest no-show probability. Appointment time later in the day (after 4:30 pm) is more likely to be no-show than earlier appointments (before 10:30 am). Regarding the distance, the patients scheduled for the bariatric surgeons who lived more than 50 km away missed more appointments (OR = 1.36). There was no uniformity among the specialties regarding weekday and month. Age group, gender, and insurance payment were not significantly associated with non-attendance across the team.

In addition, we analyzed statistically the relationship between the type of appointment and other variables: we used the pre-surgery × post-surgery as the dependent variable, in order to understand their differences. Older patients, women, and patients who have health insurance tend to schedule more post-surgery appointments than younger ones, men, and those who pay for their own appointment, respectively.

Table 1 Descriptive characteristics of the study population (N = 13,320)

Independent variables	No-show N (%)	Show N (%)	Total N
Age group			
14 to 29 years	451 (22.3%)	1567 (77.7%)	2018
30 to 44 years	1608 (23.4%)	5278 (76.6%)	6886
45 to 59 years	638 (19.2%)	2685 (80.8%)	3323
More than 59 years	113 (17.5%)	534 (82.5%)	647
Gender			
Female	2118 (22.0%)	7491 (78.0%)	9609
Male	591 (20.1%)	2345 (79.9%)	2936
Form of payment			
Self-pay	1402 (20.7%)	5385 (79.3%)	6787
Health insurance	1495 (23.2%)	4948 (76.8%)	6443
Specialty			
Bariatric surgeon	1244 (25.7%)	3591 (74.3%)	4835
Psychologist	470 (18.5%)	2066 (81.5%)	2536
Nutritionist	474 (19.3%)	1976 (80.7%)	2450
General practitioner	302 (19.2%)	1268 (80.8%)	1570
Endocrinologist	407 (22.1%)	1432 (77.9%)	1839
Lead time			
0 to 7 days	915 (18.5%)	4020 (81.5%)	4935
8 to 15 days	930 (23.9%)	2969 (76.1%)	3899
16 to 29 days	805 (24.0%)	2549 (76.0%)	3354
More than 29 days	245 (23.6%)	792 (76.4%)	1037
Appointment time			
08:30 am to 10:30 am	609 (20.2%)	2411 (79.8%)	3020
10:31 am to 12:30 pm	542 (20.0%)	2164 (80.0%)	2706
12:31 pm to 2:30 pm	580 (20.7%)	2218 (79.3%)	2798
2:31 pm to 4:30 pm	615 (19.4%)	2547 (80.6%)	3162
4:31 pm to 6:30 pm	551 (35.7%)	993 (64.3%)	1544
Prior no-show history			
0 to 10%	683 (13.0%)	4558 (87.0%)	5241
10 to 30%	495 (17.3%)	2374 (82.7%)	2869
30 to 50%	275 (27.7%)	719 (72.3%)	994
More than 50%	614 (41.9%)	852 (58.1%)	1466
Number of previous appointments			
0 to 2 times	1422 (27.3%)	3790 (72.7%)	5212
3 to 9 times	829 (18.8%)	3576 (81.2%)	4405
More than 9 times	646 (17.9%)	2967 (82.1%)	3613
Type of appointment			
Pre-surgery (first appointments)	712 (26.8%)	1948 (73.2%)	2660
Pre-surgery (other appointments)	568 (14.7%)	3308 (85.3%)	3876
Post-surgery	1046 (21.9%)	3723 (78.1%)	4769
Appointment weekday			
Monday	834 (24.5%)	2574 (75.5%)	3408
Tuesday	610 (20.0%)	2434 (80.0%)	3044
Wednesday	793 (22.2%)	2785 (77.8%)	3578
Thursday	378 (23.8%)	1212 (76.2%)	1590
Friday	282 (17.5%)	1328 (82.5%)	1610
Distance			
Less than 10 km	613 (20.4%)	2388 (79.6%)	3001
10 to 20 km	323 (18.7%)	1407 (81.3%)	1730
20 to 50 km	1421 (23.4%)	4660 (76.6%)	6081
More than 50 km	298 (21.5%)	1090 (78.5%)	1388
Appointment month			
Dec-Jan-Feb	669 (19.8%)	2708 (80.2%)	3377
Mar-Apr-May	1008 (21.6%)	3652 (78.4%)	4660
Jun-Jul-Aug	576 (21.7%)	2083 (78.3%)	2659
Sep-Oct-Nov	644 (25.4%)	1890 (74.6%)	2534

Discussion

The interest of the healthcare community in understanding the issues involved in no-show behavior and risk factors is growing in various clinical settings. In this study, we considered the no-show as a dependent variable, in which the patient neither arrives at his/her appointment nor cancels it. The objectives of this work were to find the risk factors and the coefficients required to calculate each patient's no-show probability using a logistic regression model and to suggest some changes in the current process to decrease no-shows.

We investigated the factors related to no-show of 13,230 appointments in a bariatric surgery clinic over a 17-month period with the overall no-show of 21.9%. From a logistic model, we found that the specialty, lead time, the hour of the day, previous no-show history, number of previous appointments, type of appointment, distance, and month were significantly associated with no-shows.

The prior no-show history was found to be the strongest predictor: patients who had missed previous appointments were more likely to miss their next one. This effect is consistent with the literature on other types of clinic [10, 19–21]. Moreover, patients with fewer previous appointments were more likely to miss appointments, a finding in line with existing results [22–24]. In a recent systematic literature review (SLR) [17], Dantas et al. revealed that of the 17 articles that analyzed the previous no-show history, only two did not find it significant.

According to the findings, lead time showed a significant effect in predicting no-show behavior [4, 19, 25]. In this case, patients with up to 1 week (0 to 7 days) of lead time were less likely to miss their appointments, and there was not much difference between the other lead time groups. Therefore, reminder phone calls prior to the appointment are very important, mainly for patients who scheduled more than a week in advance.

This article also shows that patients with appointments in December, January, or February (summer season in Brazil) are more likely to show up. This latter finding was not consistent with other settings [8, 26]. Our hypothesis is that patients are more available to go the doctor during these months since it is usually a vacation period in Brazil.

The no-show was higher for appointments after the surgery when compared to appointments before the surgery [15, 27]. Patients scheduled for post-surgery appointments miss 1.58 times more than pre-surgery. This supports the observations of Toussi et al.: pre-surgical and obese patients tend to adhere more to lifestyle changes because they want the surgery [15]. Although the same number of post-surgical appointments is recommended for all patients, the older patients, women, and patients who have health insurance tend to schedule more post-surgery appointments than the others.

Gender was not a significant predictor [13, 14, 27] and no differences were seen in terms of age [27]. The form of

Table 2 Univariate and multiple analysis, including coefficients (β), odds ratio (OR), OR with 95% confidence intervals, and p values

Independent variable (reference level)	Univariate (α=0.25)				Multiple (α=0.05)				Reduced Multiple (α=0.05)			
	ß	OR	OR 95% CI	p value	ß	OR	OR 95% CI	p value	ß	OR	OR 95% CI	p value
Intercept					− 2.422				− 2.508			
Age group (14 to 29 years)												
30 to 44 years	0.138	1.14	(0.96–1.36)	0.109	0.052	1.05	(0.88–1.26)	0.563				
45 to 59 years	− 0.048	0.95	(0.78–1.15)	0.621	− 0.075	0.92	(0.75–1.13)	0.465				
More than 60 years	− 0.071	0.93	(0.67–1.28)	0.667	− 0.114	0.89	(0.63–1.25)	0.515				
Gender (female)												
Male	− 0.174	0.84	(0.72–0.96)	0.015	− 0.119	0.88	(0.76–1.03)	0.118				
Form of payment (health insurance)												
Self-pay	− 0.058	0.94	(0.83–1.05)	0.322								
Specialty (bariatric surgeon)												
Psychologist	− 0.085	0.91	(0.77–1.08)	0.305	0.226	1.25	(1.03–1.51)	0.019	0.231	1.26	(1.04–1.51)	0.013
Nutritionist	− 0.087	0.91	(0.77–1.08)	0.304	0.037	1.03	(0.85–1.25)	0.699	0.060	1.06	(0.88–1.28)	0.520
General practitioner	− 0.087	0.91	(0.75–1.11)	0.374	0.145	1.15	(0.93–1.43)	0.186	0.205	1.22	(0.99–1.51)	0.055
Endocrinologist	0.154	1.16	(0.97–1.40)	0.098	0.201	1.22	(0.99–1.49)	0.051	0.208	1.23	(1.00–1.50)	0.040
Lead time (0 to 7 days)												
8 to 15 days	0.410	1.50	(1.30–1.74)	< 0.001	0.352	1.42	(1.22–1.65)	< 0.001	0.351	1.42	(1.22–1.65)	< 0.001
16 to 29 days	0.400	1.49	(1.28–1.73)	< 0.001	0.325	1.38	(1.17–1.62)	< 0.001	0.323	1.38	(1.17–1.62)	< 0.001
More than 30 days	0.391	1.47	(1.18–1.84)	< 0.001	0.381	1.46	(1.15–1.85)	0.001	0.368	1.44	(1.13–1.83)	0.002
Appointment time (08:30 am to 10:30 am)												
10:31 am to 12:30 pm	− 0.085	0.91	(0.77–1.09)	0.329	− 0.055	0.94	(0.79–1.13)	0.546	− 0.052	0.94	(0.79–1.13)	0.562
12:31 pm to 2:30 pm	− 0.149	0.86	(0.72–1.02)	0.093	− 0.152	0.85	(0.71–1.03)	0.105	− 0.137	0.87	(0.72–1.04)	0.140
2:31 pm to 4:30 pm	− 0.213	0.80	(0.68–0.95)	0.015	− 0.102	0.90	(0.75–1.08)	0.269	−0.111	0.89	(0.74–1.07)	0.223
4:31 pm to 6:30 pm	0.613	1.84	(1.51–2.25)	< 0.001	0.782	2.18	(1.75–2.72)	< 0.001	0.768	2.15	(1.73–2.68)	< 0.001
Prior no-show history (0 to 10%)												
10 to 30%	0.237	1.26	(1.08–1.47)	0.002	0.291	1.33	(1.13–1.58)	< 0.001	0.297	1.34	(1.13–1.59)	< 0.001
30 to 50%	0.903	2.46	(2.03–2.99)	< 0.001	0.992	2.69	(2.18–3.32)	< 0.001	1.009	2.74	(2.22–3.37)	< 0.001
More than 50%	1.518	4.56	(3.90–5.33)	< 0.001	1.506	4.51	(3.82–5.31)	< 0.001	− 0.256	4.58	(3.89–5.40)	< 0.001
Number of previous appointments (1 or 2 times)												
3 to 9 times	− 0.268	0.76	(0.66–0.88)	< 0.001	− 0.180	0.83	(0.70–0.99)	0.040	− 0.183	0.83	(0.70–0.98)	0.036
More than 10 times	− 0.337	0.71	(0.61–0.82)	< 0.001	− 0.244	0.78	(0.64–0.95)	0.013	− 0.256	0.77	(0.63–0.93)	0.008
Type of appointment (pre-surgery)												
Post-surgery	0.204	1.22	(1.09–1.37)	< 0.001	0.447	1.56	(1.36–1.79)	< 0.001	0.461	1.58	(1.38–1.82)	< 0.001
Appointment weekday (Monday)												
Tuesday	− 0.035	0.96	(0.81–1.13)	0.668	− 0.043	0.95	(0.80–1.14)	0.629				
Wednesday	− 0.136	0.87	(0.73–1.03)	0.110	− 0.164	0.84	(0.70–1.01)	0.072				
Thursday	0.159	1.17	(0.97–1.41)	0.099	0.161	1.17	(0.95–1.44)	0.121				
Friday	− 0.283	0.75	(0.61–0.92)	0.006	− 0.189	0.82	(0.66–1.03)	0.094				
Distance (less than 10 km)												
10 to 20 km	− 0.208	0.81	(0.65–0.99)	0.047	− 0.157	0.85	(0.68–1.06)	0.154	− 0.170	0.84	(0.67–1.04)	0.122
20 to 50 km	0.138	1.14	(0.99–1.32)	0.058	0.175	1.19	(1.02–1.38)	0.024	0.172	1.18	(1.02–1.38)	0.026
More than 50 km	− 0.051	0.95	(0.76–1.17)	0.638	− 0.037	0.96	(0.76–1.20)	0.746	− 0.018	0.98	(0.78–1.22)	0.874
Appointment month (Dec-Jan-Feb)												
Mar-Apr-May	0.052	1.05	(0.89–1.23)	0.512	0.084	1.08	(0.92–1.28)	0.319	0.066	1.06	(0.90–1.26)	0.432
Jun-Jul-Aug	0.181	1.19	(1.00–1.42)	0.039	0.152	1.16	(0.97–1.39)	0.102	0.153	1.16	(0.97–1.39)	0.098
Sep-Oct-Nov	0.358	1.43	(1.20–1.70)	< 0.001	0.273	1.31	(1.09–1.57)	0.003	0.272	1.31	(1.09–1.57)	0.003

payment for medical services was not found to be a significant predictor of no-shows [10, 28], but was significant when compared to the type of visit (before and after surgery).

In our work, the travel distance to the bariatric surgery center appeared to be significant. Sivagnanam and Rhodes affirm that with increasing distance to the clinic, patients in treatments of morbid obesity attend fewer appointments [29]. However, our results showed that patients who live more than 50 km away appear more than those living less than 10 km away.

In the stratified specialties analyses, the effect of variables, except previous no-show history, was not uniform. This may happen, for example, because the providers work at different times and days. Moreover, the variations can be due to the urgency and duration of treatment being different across specialties. The individual analysis can help to better understand these differences.

There are some limitations to our study. As this work was conducted for appointments of patients interested in bariatric surgery at a single clinic, we cannot yet claim that the prediction models developed can be generalized to other clinic settings. However, the methods described and the analytical process can be adapted or extended.

Our findings are useful to providers and clinic administrators. Knowledge of how certain factors impact no-show behavior is important when devising interventions to mitigate the negative effects of missed appointments on provider productivity and clinic efficiency. The results put forth in this empirical study can be used to change scheduling policies, such as overbooking, and to develop a dynamic scheduling system that considers each patient's no-show probability. Some examples of the relevance of no-show studies can also be seen in the literature [9–11]. Being able to predict each patient's no-show can help reduce healthcare expenditure and idle time while improving the quality and efficiency of care.

A possible future research is to compare the clinical system before and after deploying a dynamic scheduling system that considers each patient's no-show probability by using these statistical models.

In addition to the development of a dynamic scheduling system, we are already able to suggest some changes in the current process. Firstly, the clinic should improve its appointment scheduling policies, considering the preference of each patient for days and times, instead of using the fixed slots for each provider. Moreover, if a patient misses an appointment, the reasons related to the no-show should be evaluated and explored. Collecting these data will make it possible to devise improvement strategies for the booking system and treatment of the patient.

Also, appointment reminders prior to the visit must be sent. Many studies analyzed the cost-effectiveness of different confirmation reminders (SMS, email, phone call, among others) and affirm that this practice drastically reduces no-show rates [5, 30, 31]. In the investigated clinic, the confirmation reminder by messages is a very effective parameter in attendance to reduce forgetfulness. However, phone call reminders should also be used for patients with high no-show probability.

Exploring specific factors related to patient no-shows help to reduce problems that affect all specialties. For example, we can see that long lead time is a significant problem in this clinic, since patients with more than a week of lead time were more likely to miss their appointments. Therefore, confirmation reminders prior to the appointment are essential, mainly for these patients, and the clinic should try to make appointments for earlier dates. Other factors such as appointment time and weekday should also be analyzed before a booking.

Adapting schedules according to patient availability, sending reminders, and evaluating why patients are missing their appointments will reduce non-attendance rates. Besides improving clinic revenue, these actions may avoid the discontinuity of treatment by the patient, preventing future health problems.

Acknowledgments The authors would like to thank all the staff from the clinic for their help with data collection.

Funding This work was supported by the National Council for Scientific and Technological Development (CNPq) [grant numbers 169049/2017-5 to LFD, 306802/2015-5 and 403863/2016-3 to SH, 443595/2014-3 and 304843/2016-4 to FLCO, and 309828/2015-5 and 453996/2014-0 to SDJB]; the Carlos Chagas Filho Foundation (FAPERJ) [grant number E-26/202.806/2015 to FLCO]; the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001; and the Pontifical Catholic University of Rio de Janeiro.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval Statement This article does not contain any studies with human participants or animals performed by any of the authors. For this type of study, formal consent is not required.

Informed Consent Statement Does not apply.

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