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Identification of children at risk of missing telemedicine appointments: development of a predictive model during the COVID-19 pandemic

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ABSTRACT

Introduction. Although the use of telemedicine appointments has grown exponentially since the COVID-19 pandemic, missed telemedicine appointments remain a relatively understudied topic. We set out to develop and validate a predictive model to identify patients at high risk of missing telemedicine appointments.

Methods. Retrospective cohort. We included telemedicine appointments from August 1, 2020, to March 31, 2021. We included as predictors the clinical characteristics of the patients, missed appointment history, appointment characteristics, social determinants of health, and weather conditions. We developed a predictive model using multivariate mixed-effects logistic regression

Results. We included 3339 telemedicine appointments, with a missed appointment rate of 11.35% (95%CI 10.3-12.5). Among the risk factors for missing telemedicine appointments, we found that public health coverage (OR 2.2) and having other appointments on the same day (OR 3.2) increased the likelihood of missing telemedicine appointments. On the other hand, having a chronic condition (OR 0.5) and the number of previous appointments requested (OR 0.7) acted as protective factors. The final predictive model included 19 variables and 4 interactions, with an area under the ROC curve of 0.72 (95%CI 0.7-0.8) and a calibration slope of 0.78 (95%CI 0.6-0.9), indicating slight overfitting.

Conclusion. In this study, we developed and validated a predictive model that identifies children at high risk of missing telemedicine appointments. This model helps guide strategies aimed at reducing missed telemedicine appointments.

Keywords: *telemedicine; prediction algorithms; missed appointment; no-show; children; covid-19.*

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INTRODUCTION

Missed appointments in pediatrics poses a significant challenge, as it is associated with poorer patient health outcomes[1-3] and contributes to increased healthcare costs, primarily due to lost income.[4,5] Furthermore, it perpetuates existing inequalities in access to health care because patients from disadvantaged socioeconomic backgrounds are more likely to miss their scheduled appointments.[6]

Since the COVID-19 pandemic, telemedicine appointments have experienced a significant increase. Although their integration into pediatric practice is expected to continue growing,[7,8] research on missed telemedicine appointments is still scarce. This knowledge gap contrasts with the extensive evidence on in-person appointments, where missed appointment rates average 23%.[9] Understanding the phenomenon in the virtual context is therefore essential.

While strategies exist to reduce missed appointments, their universal implementation (e.g., sending reminders to each patient) is costly and inefficient.[10,11] This is where predictive models emerge as a tool with high potential. These models enable appointments to be identified and stratified according to their probability of no-show,[12,13] facilitating the implementation of targeted and cost-effective interventions aimed solely at patients at higher risk of no-show.

Considering the increase in pediatric telemedicine appointments since the COVID-19 pandemic and the lack of information on the results of their implementation, our objective was to estimate the no-show rate for telemedicine appointments during the COVID-19 pandemic at the Hospital General de Niños Pedro Elizalde (HGNPE), identify whether there were any associated explanatory factors, and to develop and validate a predictive model missed appointment telemedicine appointments.

METHODS

Retrospective cohort study. We included all pediatric telemedicine appointments scheduled for patients aged 1 month to 18 years at the HGNPE between August 1, 2020, and March 31, 2021. We excluded spontaneous telemedicine appointments. The HGNPE, a pediatric center in the City of Buenos Aires, primarily serves patients from the Metropolitan Area of Buenos Aires. For outpatient care, it uses an electronic medical record (EMR) system. During the COVID-19 pandemic, telemedicine (utilizing only video calls or phone calls) was implemented to ensure continuity of care. The unit of analysis was the scheduled telemedicine appointment. The outcome variable was missed appointment. We categorized all scheduled telemedicine appointments that did not take place as missed, regardless of the reason for non-attendance. Cancellations could not be distinguished, as the appointment system did not have a cancellation option.

We evaluated potential predictors of missed telemedicine appointments from the following domains:

1. **Baseline characteristics of patients:** Includes demographic and administrative variables that construct an initial risk profile for the patient.
2. **Appointment request process:** Includes variables related to appointment management, such as the time frame in which the request was made. A more extended period between the request and the appointment is a known risk factor that increases the likelihood of forgetfulness.
3. **Patient appointment history:** Describes the patient's historical behavior regarding previous appointments (in-person and telemedicine). A patient's previous behavior is a strong predictor of future behavior.
4. **Characteristics of the scheduled telemedicine appointment:** Contains specific information about the appointment, such as the day, time, and specialty. Its inclusion allows the model to identify temporal and logistical patterns, as specific schedules or overlaps with other appointments can create scheduling conflicts that increase the risk of no-show.
5. **Clinical characteristics and comorbidities of the patient:** Summarizes the patient's health condition, highlighting the presence of chronic diseases.
6. **Social determinants of health:** Incorporates socioeconomic and demographic population indicators to contextualize the environment of patients and their families. We decided to evaluate variables such as the proportion of older adults or women of childbearing age because, in the absence of individual data on family structure in the medical record, these indicators serve as proxies for the patient's environment.
7. **Weather characteristics:** Includes meteorological variables on the day of the

appointment to explore whether weather conditions influence telemedicine appointment attendance.

8. **Social isolation:** Periods of isolation (ASPO, by its Spanish acronym)[14] and social distancing (DISPO, by its Spanish acronym)[15] during the pandemic. Provides information on changes in social behavior and access to healthcare.

We include as supplementary material the complete and detailed operationalization of all study variables.

We extracted administrative and clinical information from the EMR. We requested weather variables from the National Weather Service.[16] Retrospective data on social determinants of health are often absent from medical records.[17] To overcome this problem, we constructed predictors of social determinants using data from the 2010 National Population, Household, and Housing Census[18] aggregated at the smallest geographical unit available which groups an average of 300 households. We assigned the corresponding geographical unit to each patient using georeferencing.

Statistical analysis

We randomly divided the sample into two groups: a generation group (comprising two-thirds of the sample) and a validation group (comprising one-third of the sample). In the generation group, we evaluated the univariate association between each potential predictor and no-show using a mixed-effects logistic regression model, considering the natural grouping of scheduled telemedicine appointments for the same patient. We used a random intercept (random effect) and each factor as a fixed effect. We estimated the odds ratios (ORs) along with their 95% confidence intervals (95%CIs) and *p*-values for missed telemedicine appointments.

We incorporated the significant variables identified in the univariate analysis, along with all those considered relevant, to generate several alternative models. We evaluated the collinearity between predictors graphically and with Pearson's correlation coefficient. We assessed the presence of interaction using interaction terms only for combinations of two variables that showed clinical significance, as determined by the research team. We excluded collinear variables and considered only interactions that were significant for inclusion in the models. We evaluated the reliability of the model quadrature estimate and considered only models with relative differences of less than 0.01 for each estimated parameter as candidates. We compared the different alternative predictive models using the Akaike information criterion (AIC) and the diagnostic performance of the model using ROC curves. Finally, we selected the model with the most significant area under the ROC curve and the lowest AIC.

We validated the selected model by estimating discrimination (area under the ROC curve) and calibration (calibration in the large [CITL] and calibration slope) in both the generation and validation datasets.[19] CITL compares the mean predicted probabilities with the mean observed probabilities. When CITL >0, the model underestimates the probability of no-show (the observed probability of no-show is greater than that predicted by the model). When CITL <0, the model overestimates the probability of no-show (the probability predicted by the model is greater than that observed). The calibration slope indicates whether calibration is maintained across the entire range of observations. A slope <1 indicates overfitting. Conversely, a slope greater than 1 suggests underfitting.

We considered a *p*-value <0.05 to be significant. Statistical analysis was performed using STATA® software, version 16 (StataCorp, Texas, USA).

Ethical considerations

The data were anonymized to protect patient privacy and confidentiality. The protocol was approved by the Institutional Research Ethics Committee (registration number 2392) and registered at ClinicalTrials.gov (NCT04736680).

RESULTS

We included 3339 scheduled telemedicine appointments from 2378 patients, with an average of 1.4 scheduled telemedicine appointments per patient. We randomly assigned 2226 telemedicine appointments to the generation group and 1113 to the validation group. The flow of telemedicine appointments inclusion is shown in *Figure 1*.

The median age of the patients was 6.37 years, with no predominance of biological sex. Most patients were residents outside the Autonomous City of Buenos Aires (CABA, by its Spanish acronym) (median distance to HGNPE of 21 km) and had exclusive public health insurance.

Table 1 details the characteristics of the telemedicine appointments. *Table S-1* in the supplementary material provides an overview of the baseline characteristics of patients.

Table 1. Characteristics of telemedicine appointments

	Total (n=3339)	Attended (n=2960)	Missed (n=379)
Patient baseline characteristics			
Age. years [a]	6.4 (2.7-11.3)	6.3 (2.6-11.4)	6.5 (2.9-10.6)
Female sex	1668 (49.9%)	1490 (50.3%)	178 (46.9%)
Address in CABA	1045 (31.3%)	882 (29.8%)	163 (43.1%)
Public health insurance	2436 (72.9%)	2122 (71.6%)	314 (82.9%)
Number of medical conditions in the Electronic Medical Record [a]	2 (1-4)	2 (1-5)	1(1-3)
Distance from the patient's home to hospital. kilometers [a]	21 (7-28)	21 (7-28)	16 (6-27)
Travel time from the patient's home to hospital. minutes [a]	25 (14-37)	25 (14-37)	22 (13-37)
Appointment request process			
Telemedicine appointment requested in -person	3063 (91.7%)	2745 (92.7%)	318 (83.9%)
Lead time to the telemedicine appointment [a]	1.81 (0.16-5.81)	1.75 (0.11-5.44)	2.00 (1.00-6.85)
Communication modality requested			
Phone call	1455 (85.9%)	1299 (87.5%)	156 (74.6%)
Video call	239 (14.1%)	186 (12.5%)	53 (25.4%)
Patient appointment history			
Number of previously requested appointments for each telemedicine appointment [a]	1 (0-4)	1 (0-4)	1 (0-2)
Percentage of previous missed appointments for each telemedicine appointment [a]	0 (0-0)	0 (0-0)	0 (0-0)
Number of previous telemedicine appointments requested to each telemedicine appointment [a]	0 (0-1)	0 (0-1)	0 (0-0)
Percentage of previous missed telemedicine appointments to each telemedicine appointment [a]	0 (0-0)	0 (0-0)	0 (0-0)
Number of previous in-person appointments requested for each telemedicine appointment [a]	1 (0-3)	1 (0-3)	1 (0-2)
Percentage of previous in-person missed appointments to each telemedicine appointment [a]	0 (0-0)	0 (0-0)	0 (0-0)
Hospitalization during scheduled telemedicine appointment	41 (1.2%)	38 (1.3%)	3 (0.8%)
Hospitalization prior to scheduled telemedicine appointment	546 (16.35%)	497 (16.8%)	49 (12.9%)
Death prior to scheduled telemedicine appointment	0 (0.0%)	0 (0.0%)	0 (0.0%)
Characteristics of the scheduled telemedicine appointment			
First-time telemedicine appointment	2241 (67.1%)	1966 (66.4%)	275 (72.6%)
Hour of the day			
8	506 (15.2%)	456 (15.4%)	50 (13.2%)
9	636 (19.1%)	558 (18.9%)	78 (20.6%)
10	590 (17.7%)	528 (17.8%)	62 (16.4%)
11	715 (21.4%)	637 (21.5%)	78 (20.6%)
12	336 (10.1%)	300 (10.1%)	36 (9.5%)
13	344 (10.3%)	303 (10.2%)	41 (10.8%)
14 or later	212 (6.4%)	178 (6.0%)	34 (8.9%)
High missed appointment hours	817 (24.5%)	705 (23.8%)	112 (29.6%)
Day of the week			
Monday	800 (23.9%)	699 (23.6%)	101 (26.7%)
Tuesday	540 (16.2%)	495 (16.7%)	45 (11.9%)
Wednesday	764 (22.9%)	692 (23.4%)	72 (19.0%)
Thursday	636 (19.1%)	554 (18.7%)	82 (21.6%)
Friday	599 (17.9%)	520 (17.6%)	79 (20.8%)
High missed appointment days	2035 (60.9%)	1773 (59.9%)	262 (69.1%)
Month			
January	420 (12.6%)	371 (12.5%)	49 (12.9%)
February	344 (10.3%)	279 (9.4%)	65 (17.2%)
March	254 (7.6%)	226 (7.6%)	28 (7.4%)
April	273 (8.2%)	251 (8.5%)	22 (5.8%)
August	545 (16.3%)	515 (17.4%)	30 (7.9%)
September	587 (17.6%)	549 (18.6%)	38 (10.0%)
October	444 (13.3%)	353 (11.9%)	91 (24.0%)

	November	202 (6.1%)	171 (5.8%)	31 (8.2%)
	December	270 (8.1%)	245 (8.3%)	25 (6.6%)
High missed appointment month		546 (16.4%)	450 (15.2%)	96 (25.3%)
Another appointment on the same day at the hospital		478 (14.3%)	389 (13.1%)	89 (23.5%)
Another appointment on the same day at any medical office in X City		21 (0.6%)	18 (0.6%)	3 (0.8%)
Other visit at the same time and day at the hospital		8 (0.2%)	6 (0.2%)	2 (0.5%)
Other visit at the same time and day at any other medical office in X City		1 (0.0%)	1 (0.0%)	0 (0.0%)
Pediatric subspecialty				
	General pediatrics	1917 (57.4%)	1662 (56.2%)	255 (67.3%)
	Adolescence	149 (4.5%)	131 (4.4%)	18 (4.8%)
	Rheumatology	120 (3.6%)	117 (3.9%)	3 (0.8%)
	Nephrology	128 (3.8%)	122 (4.1%)	6 (1.6%)
	Immunology	105 (3.1%)	102 (3.5%)	3 (0.8%)
	Pneumology	216 (6.5%)	187 (6.3%)	29 (7.7%)
	Otorhinolaryngology	279 (8.4%)	245 (8.3%)	34 (8.9%)
	Dermatology	118 (3.5%)	104 (3.5%)	14 (3.7%)
	Mental Health	138 (4.1%)	131 (4.4%)	7 (1.9%)
	Other	169 (5.1%)	159 (5.4%)	10 (2.6%)
High missed appointment subspecialty		2605 (78.0%)	2263 (76.5%)	342 (90.2%)
Clinical characteristics and comorbidities of the patient				
Chronic disease		1723 (51.6%)	1574 (53.2%)	149 (39.3%)
Infectious disease		1345 (40.3%)	1216 (41.1%)	129 (34.0%)
Medical conditions related to COVID-19		1002 (30.0%)	900 (30.4%)	102 (26.9%)
Neurologic disease		533 (15.9%)	482 (16.3%)	52 (13.5%)
Respiratory system disease		485 (14.5%)	435 (14.7%)	50 (13.2%)
Cardiological disease		476 (14.3%)	439 (14.8%)	37 (9.8%)
Mental Health		330 (9.9%)	303 (10.2%)	27 (7.1%)
Dermatological diseases		314 (9.4%)	291 (9.8%)	23 (6.1%)
Neurodevelopmental disorders		237 (7.1%)	212 (7.2%)	25 (6.6%)
Genitourinary system disease		272 (8.2%)	260 (8.8%)	12 (3.2%)
Gastroenterological disease		240 (7.2%)	224 (7.6%)	16 (4.2%)
Social services follow-up		242 (7.3%)	220 (7.4%)	22 (5.8%)
Allergic disease		230 (6.9%)	222 (7.5%)	8 (2.1%)
Otorhinolaryngological disease		163 (4.9%)	152 (5.1%)	11 (2.9%)
Onco-hematological disease		179 (5.4%)	170 (5.7%)	9 (2.4%)
Trauma disease		136 (4.1%)	128 (4.3%)	8 (2.1%)
Rheumatological disease		131 (3.9%)	126 (4.3%)	5 (1.3%)
Immunological disease		135 (4.0%)	130 (4.4%)	5 (1.3%)
Endocrinological disease		133 (3.9%)	130 (4.4%)	3 (0.8%)
Gynecological disease		93 (2.8%)	87 (2.9%)	6 (1.6%)
Genetic disease		73 (2.2%)	70 (2.4%)	3 (0.8%)
Social determinants of health				
Percentage of population aged 65 years or above [b]		13.16 (6.56)	13.12 (6.55)	13.49 (6.65)
Percentage of the population aged 80 years or above [a]		3.53 (1.68-5.30)	3.48 (1.68-5.30)	3.89 (1.68-5.30)
Percentage of the population under 5 years old [b]		27.28 (9.18)	27.26 (9.09)	27.44 (9.87)
Aging index [a]		74.8 (32.23-104.19)	72.43 (32.23-103.31)	83.98 (33.00-112.79)
Percentage of women of childbearing age [b]		49.52 (5.24)	49.53 (5.24)	49.45 (5.25)
Percentage of foreign-born population [a]		6.59 (4.60-12.93)	6.59 (4.56-12.46)	8.47 (4.94-16.14)
Illiteracy rate [a]		0.70 (0.32-1.64)	0.70 (0.33-1.63)	0.68 (0.27-1.77)
Proportion of the population who has never attended school [a]		1.39 (0.75-2.64)	1.39 (0.75-2.64)	1.48 (0.75-2.63)
Proportion of the population with tertiary/higher education [a]		20.75 (8.16-34.67)	20.75 (8.16-34.67)	21.12 (8.92-34.95)
Proportion of the population that uses a computer [b]		61.38 (12.65)	61.30 (12.53)	62.03 (13.50)
Percentage of households with critical overcrowding [a]		1.77 (0.63-5.32)	1.68 (0.63-5.32)	1.77 (0.63-5.32)
Percentage of households with running water [a]		97.65 (88.37-99.23)	97.65 (88.37-99.23)	97.65 (88.37-99.26)
Percentage of households without toilets connected to a public sewerage network [a]		8.11 (0.77-93.23)	9.49 (0.85-94.35)	3.7 (0.45-72.22)
Percentage of households with unsatisfied basic needs [a]		5.63 (1.91-19.27)	5.63 (1.91-19.27)	5.75 (1.62-19.27)

Potential dependence index [b]	51.42 (6.7)	51.42 (6.67)	51.43 (7.06)
Activity rate [b]	70.23 (4.37)	70.21 (4.38)	70.41 (4.31)
Unemployment rate [b]	5.85 (2.81)	5.87 (2.84)	5.77 (2.48)
Employment rate [b]	66.14 (4.92)	66.12 (4.96)	66.35 (4.62)
Weather conditions			
Maximum daily temperature in ºC [b]	24.23 (5.41)	24.16 (5.49)	24.76 (4.70)
Minimum daily temperature in ºC [b]	15.16 (4.54)	14.58 (5.55)	15.16 (4.54)
Average daily temperature in ºC [b]	19.29 (5.10)	19.22 (5.19)	19.82 (4.26)
Maximum daily thermal sensation in ºC [b]	24.21 (5.73)	24.15 (5.83)	24.66 (4.95)
Minimum daily thermal sensation in ºC [b]	14.85 (5.68)	14.78 (5.80)	15.4 (4.62)
Daily precipitations in mm [a]	0.00 (0.00-0.10)	0.00 (0.00-0.10)	0.00 (0.00-0.30)
Daily barometric pressure in hPa [b]	1012.90 (5.81)	1012.88 (5.89)	1013.10 (5.15)
Daily relative humidity in % [b]	0.65 (0.13)	0.65 (0.13)	0.66 (0.12)
Social isolation period			
Social isolation	1642 (49.2%)	1472 (49.7%)	170 (44.9%)
Social distancing	1697 (50.8%)	1488 (50.3%)	209 (55.2%)

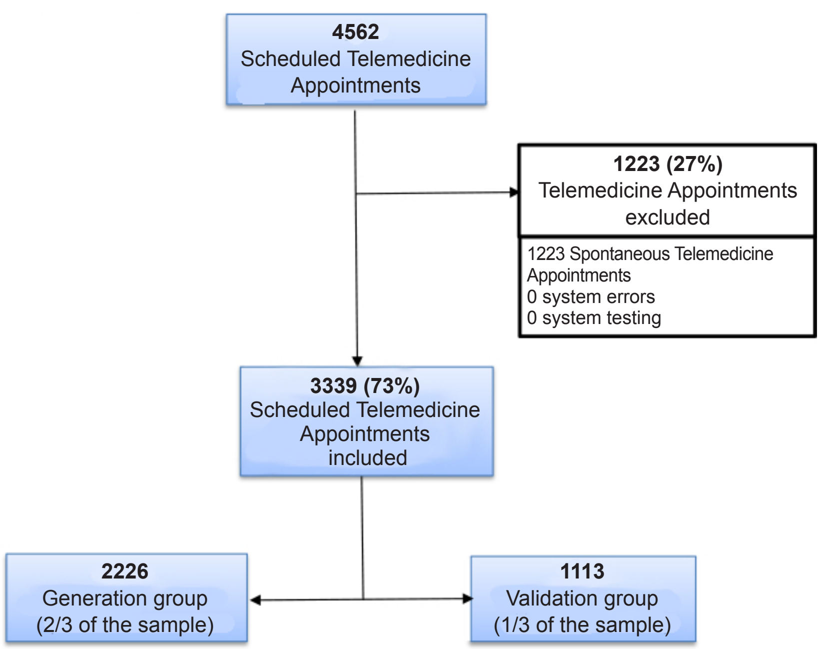
[a] Median and interquartile range.
[b] Mean and standard deviation.
CABA: Ciudad Autónoma de Buenos Aires.

Of the 3339 telemedicine appointments included, 379 were not attended (no-show rate: 11.35%, 95%CI: 10.32-12.47).

Exclusive public health insurance, address in CABA, foreign nationality, and having another appointment scheduled on the same day were associated with a higher risk of missed telemedicine appointment. We identified having a chronic condition, the number of previous telemedicine appointments, and requesting the telemedicine appointment in person as protective factors. *Figure 2* shows the main predictors evaluated. *Table S-2* in the supplementary material describes all the predictors evaluated.

The final predictive model included 19 variables, 1996 observations out of 2226 possible, an AIC of 1244.9, and an AUC of 0.77 (95%CI 0.74-0.81). The communication modality was excluded due to 50% missing data. *Table 2* presents the final predictive model.

Figure 1. Telemedicine Appointments inclusion flow



Regarding discrimination, the area under the ROC curve was 0.77 (95%CI, 0.74-0.81) in the generation group and 0.72 (95%CI, 0.67-0.77) in the validation group. *Figure 3* shows the ROC curves for the generation and validation groups. Regarding calibration, the comparison between observed and predicted values is illustrated in *Figure 3*. In the validation group,

CITL was -0.39 (95%CI: -0.79-0.01), and the calibration slope was 0.78 (95%CI 0.59-0.97).

Finally, *Table 3* shows the diagnostic performance of the model for different predicted probability cutoff points. We explored three potentially functional hypothetical scenarios by applying the missed telemedicine appointment prediction model and provided a brief description of these scenarios in the supplementary material, “Model applications.”

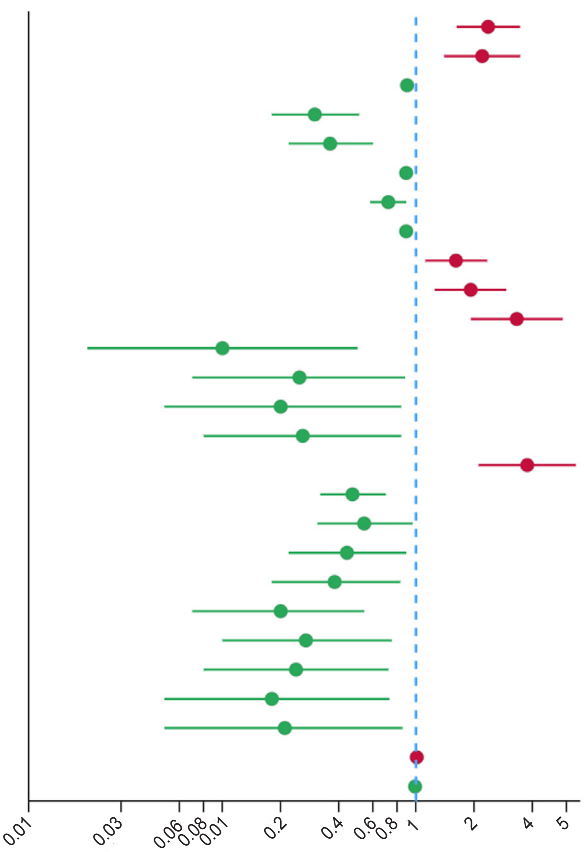
DISCUSSION

In this study, we analyzed pediatric missed telemedicine appointments during the COVID-19 pandemic in a pediatric hospital in the public healthcare network of Buenos Aires. We estimated a no-show rate of 11.35%, which is similar to the rate reported by Howie et al. (8.1%)[20] and lower than the rate reported by Chakawa et al. (25.8%).[21] Both studies were conducted in the United States. Variability in missing rates for in-person appointments is a known phenomenon that seems to be replicated in telemedicine appointments.[9] The no-show rate for telemedicine appointments during the pandemic may have been lower than that reported before the pandemic.[22]

Drerup et al. showed that the no-show rate in Ohio for telemedicine appointments during

Figure 2. Graphical representation of the effect measure of the main predictors evaluated

Predictor evaluated	OR [95%CI]
Address in CABA	2.36 [1.62 - 3.45]
Exclusive public health insurance	2.20 [1,40 -3.45]
Number of medical conditions in the Electronic Medical Record	090 [0.84 - 0.96]
Method used for the request, in-person vs. call center	0.30 [0.18 - 0.51]
Communication modality, phone call vs. video call	0.36 [0.22 - 0.60]
Number of previous appointments requested	0.89 [0.84 - 0.94]
Number of previous telemedicine appointments requested	0.72 [0.58 - 0.89]
Number of previous in-person appointments requested	0.89 [0.84 - 0.95]
High missed appointment days	1.61 [1.12 - 2.33]
High missed appointment months	1.92 [1.25 - 2.93]
Presence of other appointments on the same day at the hospital	3.32 [1.92 - 5.74]
Rheumatology subspecialty	0.10 [0.02 - 0.50]
Nephrology subspecialty	0.25 [0.07 - 0.88]
Immunology subspecialty	0.20 [0.05 - 0.84]
Mental health subspecialty	0.26 [0.08 - 0.84]
High missed appointment subspecialty	3.76 [2.11 - 8.70]
Patients with chronic diseases	0.47 [0.32 - 0.70
Cardiological diseases	0,54 [0.31 - 0.96]
Mental health disease	0.44 [0.22 - 0.89]
Skin, appendages, or stomatological diseases	0.38 [0.18 - 0.83]
Diseases of the genitourinary system	0.20 [0.07 - 0.54]
Allergic diseases	0.27 [0.10 - 0.75]
Oncohematological diseases	0.24 [0.08 - 0.72]
Rheumatological diseases	0.18 [0.05 - 0.73]
Endocrinological diseases	0.21 [0.05 - 0.85]
Percentage of population born abroad	1.01 [1.00 - 1.03]
Percentage of households without toilet drainage to the public sewer system	0,99 [0.98 - 0.99]



The blue dotted line represents no effect. Protective factors are described in green, and risk factors are represented in red. CABA: Autonomous City of Buenos Aires; CMR: comprehensive medical record.

Table 2. Final predictive model. The variables and interaction terms included are presented along with the ORs and their *p*-values

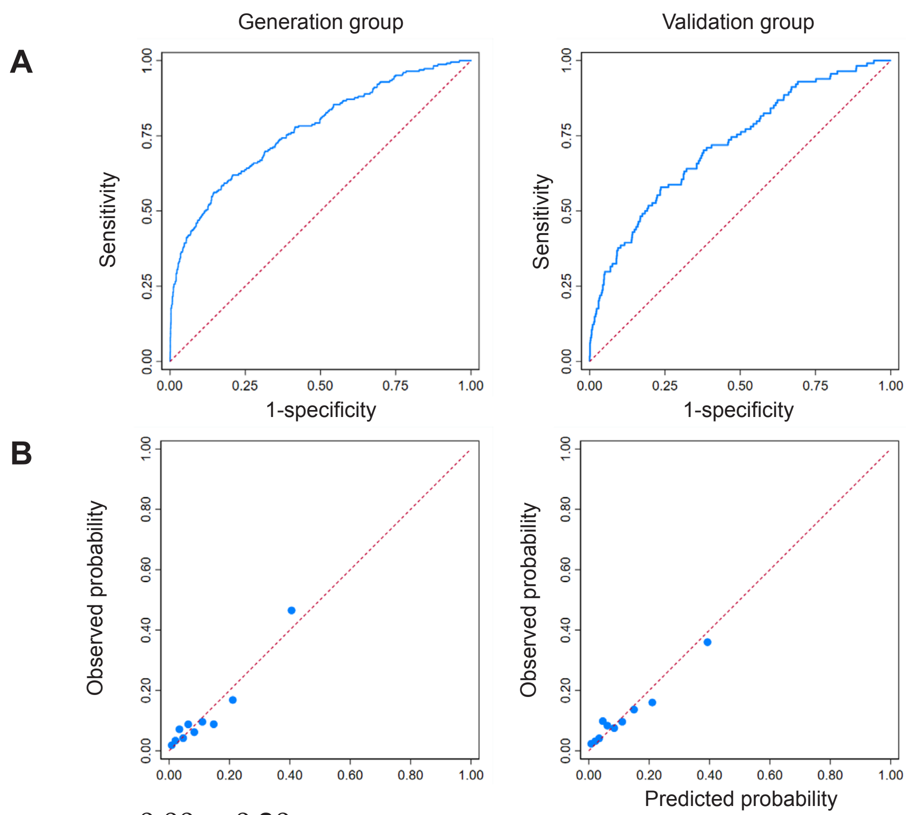
Variables		O	IC 95%	*p*
Address in CABA		0.36	0.13-1.05	0.062
Telemedicine appointment requested in -person		0.30	0.17-0.54	<0.001
Public health insurance		0.77	0.44-1.35	0.371
Chronic condition		0.28	0.12-0.64	0.003
Number of medical conditions in the Electronic Medical Record		0.84	0.71-0.99	0.042
Number of previous telemedicine appointments requested to each telemedicine appointment		0.76	0.59-0.97	0.030
Number of previously requested appointments for each telemedicine appointment		1.03	0.97-1.09	0.378
Percentage of previous missed telemedicine appointments to each telemedicine appointment		2.14	0.95-4.82	0.065
Other visits on the same day at hospital		4.34	2.87-6.57	<0.001
High missed appointment days		1.31	0.96-1.80	0.090
High missed appointment hours		1.30	0.92-1.82	0.134
Month				
	February	1.55	0.87-2.77	0.134
	March	0.95	0.47-1.91	0.883
	April	0.52	0.23-1.19	0.120
	August	0.17	0.07-0.43	<0.001
	September	0.15	0.06-0.38	<0.001
	October	0.71	0.35-1.44	0.343
	November	0.67	0.31-1.41	0.288
	December	0.96	0.48-1.91	0.901
Pediatric subspecialty				
	Adolescence	0.71	0.36-1.49	0.364
	Rheumatology	0.10	0.01-0.77	0.027
	Nephrology	0.46	0.15-1.47	0.192
	Immunology	0.43	0.11-1.61	0.210
	Pneumology	0.92	0.50-1.69	0.793
	Otorhinolaryngology	0.41	0.21-0.78	0.007
	Dermatology	0.61	0.25-1.48	0.273
	Mental health	0.24	0.08-0.76	0.015
	Other	0.47	0.14-1.53	0.209
Genitourinary system disease		0.48	0.19-1.16	0.103
Allergic disease		0.43	0.18-1.05	0.065
Percentage of the population under 5 years old		0.96	0.91-1.00	0.074
Proportion of the population who have never attended school		1.13	0.96-1.33	0.146
Potential dependence index		1.01	0.98-1.04	0.692
Minimum daily temperature in ºC		0.94	0.89-0.99	0.014
Interaction terms				
Address in X City * Telemedicine appointment requested in -person		2.82	1.25-6.40	0.012
Address in X City * Public health insurance		2.19	0.88-5.46	0.092
Chronic disease * Public health insurance		2.50	1.10-5.73	0.030
Chronic disease * Number of medical conditions in the Electronic Health Record		1.16	0.97-1.39	0.097

OR: odds ratio; 95%CI: 95% confidence interval; CABA: Autonomous City of Buenos Aires.

the pandemic was 7.5%, lower than the 29.8% reported for in-person appointments before the pandemic in the same population.[23] The estimated rate in this study is among the lowest described.[9]

Exclusive public health insurance serves as a marker of social vulnerability. It acts as a risk factor for no-show, which aligns with the findings reported in the literature for in-person appointments.[24] Although previous studies have reported an association between a history of missed appointments and a higher risk of future missed appointments, our study did not observe this association in the context of telemedicine appointments.[25] One possible explanation is that

Figure 3. A: Predicted probability ROC curves for the generation and validation groups. B: Calibration graphs of the predictive model for the generation and validation groups



0.00 0.20

the implementation of telemedicine was new in our setting, and information on patients' previous no-show history was limited.

The number of previous appointments requested, the number of problems recorded in the EMR, and the presence of chronic disease acted as protective factors against no-show. In line with our findings, Yang et al.[26] observed a decrease in the no-show rate in patients with more serious medical conditions in New Zealand. This suggests that the severity of a patient's medical condition could influence their adherence to telemedicine appointments.

Logistic regression is the most widely used strategy for developing no-show predictive moels.[27,28] We opted for a mixed-effects logistic regression model because this approach acknowledges that appointments for an individual are likely to be more similar to each other than those from different patients. To comprehensively address the study objectives, we incorporated administrative, social, clinical, and weather data. We prioritized data sources that are highly available in most healthcare settings to facilitate the potential generalization and real-world application of our findings.

Our model has an AUC of 0.77, which is similar to that reported for in-person visits in children[29] and adults.[30] When evaluating the validation of the model, the value for CITL included 0, indicating that the probabilities predicted by the model were similar to those observed in the validation group. The calibration slope was slightly less than 1, suggesting potential overfitting of the model to the validation group. Unfortunately, direct comparisons of our findings with existing literature were limited due to the scarcity of published predictive models for missed telemedicine appointments in pediatrics.[27]

This study has limitations. First, we did not study the causes of non-attendance. This could limit the practical applicability of the model, as effective interventions must be targeted at addressing the causes of non-attendance. Second, we do not have information about families. The no-show phenomenon in pediatrics is related to family and caregiver characteristics.[31,32] Third, we did not evaluate

Table 3. Diagnostic performance for different cutoff points of probability predicted by the model

Predicted probability	Sensitivity	Specificity	Positive predictive value	Negative predictive value
0.01	99.1 (95.2-100)	5.8 (4.4-7.5)	11.6 (9.7-13.8)	98.1 (90.1-100)
0.03	93.9 (87.8-97.5)	21.1 (18.5-23.9)	12.9 (10.7-15.4)	96.5 (92.9-98.6)
0.05	82.5 (74.2-88.9)	40.7 (37.5-44.0)	14.8 (12.1-17.8)	94.9 (92.9-96.9)
0.10	64.0 (54.5-72.8)	65.1 (61.9-68.2)	18.6 (14.9-22.8)	93.6 (91.4-95.3)
0.15	52.6 (43.1-62.1)	78.9 (76.1-81.5)	23.7 (18.6-29.4)	93.0 (91.0-94.7)
0.20	39.5 (30.4-49.1)	88.0 (85.7-90.0)	29.0 (22.0-36.9)	92.1 (90.1-93.8)
0.25	32.5 (24.0-41.9)	92.5 (90.5-94.1)	34.9 (25.9-44.8)	91.6 (89.7-93.4)
0.30	26.3 (18.5-35.4)	95.3 (93.7-96.6)	41.4 (29.7-53.2)	91.2 (89.2-92.9)
0.40	16.7% (10.3-24.8)	97.8 (96.6-98.7)	48.7 (32.4-65.2)	90.4 (88.4-92.2)
0.50	9.7 (4.9-16.6)	99.3 (98.6-99.8)	64.7 (38.3-85.8)	89.8 (87.8-91.6)
0.60	5.3 (1.9-11.1)	99.9 (99.4-100)	85.7 (42.1-99.6)	89.4 (87.4-91.2)
0.70	1.75 (0.2-6.2)	99.9 (99.4-100)	66.7 (9.43-99.2)	89.1 (87.0-90.9)

Sensitivity, specificity, positive predictive value, and negative predictive value are presented with their respective 95% confidence intervals.

the effect of the modality of communication due to a lack of information. Fourth, the sample size is small compared to other studies.[25] This is because the model was developed during the implementation of the system, while the studies in the literature tend to cover periods of several years.[27] Although the selection of predictors could be unstable due to a relatively small sample size, the discrimination and calibration of our model are adequate.

The study population mostly had exclusive public health insurance, therefore representing the most vulnerable strata of our society. Although this could be a selection bias, it is precisely the least studied and most vulnerable population. Considering that implementations based on information and communication technologies can perpetuate inequality in access to healthcare,[33,34] this study provides valuable insights for the design, implementation, and evaluation of public health policies that leverage information and communication technologies.

Finally, to illustrate the potential impact of our model on appointment management, we explore three practical applications in the supplementary material. Specifically, the model could be used to target reminders to patients at high risk of non-attendance (maximizing sensitivity), displaying only appointments with a high probability of attendance (maximizing the negative predictive value of non-attendance), and overbooking appointments preferably to those with the highest likelihood of non-attendance (maximizing the positive predictive value of non-attendance).

CONCLUSION

During the COVID-19 pandemic, the no-show rate for telemedicine appointments was low. We developed and validated a predictive model to identify patients at high risk of missing telemedicine appointments using administrative, clinical, social, and weather data. This model can be used to guide strategies aimed at improving adherence to appointments and optimizing the use of telemedicine. ■

The supplementary material provided with this article is presented as submitted by the authors.

It is available at: https://www.sap.org.ar/docs/publicaciones/archivosarg/2026/10749_AO_Ibarra_Anexo.pdf

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