

## Article

# No-show in medical appointments with machine learning techniques – a systematic literature review

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**Abstract:** No-show appointments in healthcare is a problem faced by medical centers around the world, and understand the factors associated with the no-show behavior is essential. In the last decades, artificial intelligence took place in the medical field and machine learning algorithms can work as a efficient tool to understand the patients behavior and to achieve better medical appointment allocation in scheduling systems. In this work, we provide a systematic literature review (SLR) of machine learning techniques applied to no-show appointments aiming at establishing the current state-of-the-art. Based on a SLR following the Kitchenham methodology, 24 articles were found and analyzed, in which the characteristics of the database, algorithms and performance metrics of each studies were synthesized. Results regarding which factors have a higher impact on missed appointment rates were analyzed too. The results indicate that the most appropriate algorithms for building the models are decision tree algorithms. Furthermore, the most significant determinants of no-show were related to the patients age, whether the patient missed a previous appointment, and the distance between the appointment and the patients scheduling.

**Keywords:** No-show; Medical Appointments; Healthcare; Artificial Intelligence; Data processing and management

## 1. Introduction

Medical appointments no-show is a problem in essentially all healthcare centers, and has a significant impact on revenues, costs and the use of resources. Also referred as missed appointments, the no-show states the patients behavior who neither attend nor cancel their medical appointments. Long waiting lines for a particular medical resource, hinders health system access to other patients and financial loss are well known consequences that the patients absence from the scheduled appointment can cause.

Previous studies have looked at the economic consequences of a patients no-show. Mesa et al. [1] pointed out that the cost for rescheduling an appointment is approximately 13 euros, and showed that in Spain, the cost generated by patients no-show was around 3 million euros. To reduce these adverse effects, health centers have implemented various strategies, including overbooking [2–4] and reminders [5–7].

Despite the development of medical scheduling systems to achieve better appointment management, the high rate of missed appointments still remains a problem. With the advent of artificial intelligence (AI) in last decades, machine learning (ML) algorithms can serve as efficient tools to understand the patients behavior and also to achieve better appointment allocation based on predictive models. As shown by Chong et al. [8], there

was a reduction from 19.3% to 15.9% in no-shows, by sending a reminder to 25% of the patients who were indicated by the predictive model at greater risk of not attending the appointment.

This paper addresses a systematic review to establish the state-of-the-art in machine learning techniques focused on no-show appointments. The review aims to identify the models that have been proposed and also which are the most widely ML algorithms used in the literature. Besides identifying each of the different ML techniques, various elements such as the characteristics of the database, algorithms employed and the performance obtained are analyzed.

We adopt the systematic literature review procedure based on the Kitchenham and Charters [9] and organize the remainder of this paper as follows. In Section 2 we detail the search protocol, including the databases selected, search criteria, and the attributes extracted from each selected studies. Next, in Section 3, the selected studies are grouped according to each research question, and the contributions of each one are highlighted. Finally, in Section 4 we discuss our findings and present the conclusions in Section 5.

## 2. Materials and Methods

In this research, we conducted a systematic literature review procedure based on the Kitchenham and Charters [9]. First, we formulated the research questions, determined the keywords, and determined the inclusion and exclusion criteria. We selected databases in the fields of health, social sciences, and computer science, determined as the most relevant fields for assessing studies related to machine learning techniques applied to patient no-shows in medical attendances. Based on the main goal of this systematic review, four research questions were developed. Each question was focused on answering one of the following topics: data volume used to train the model, machine learning algorithms, most important features that influence the no-show behavior, and the impact of using machine learning in this field. All research questions are presented in Table 1.

**Table 1.** Research Questions.

ID	Research Question
Q1	How much data is used to train machine learning models for no-show prediction?
Q2	Which machine learning algorithms are used in the predictive models and which of these presented the best performance?
Q3	What characteristics most influence patients not to attend a scheduled medical appointment?
Q4	What is the no-show rate reduction in medical appointments that solutions developed with the help of machine learning techniques achieve?

Due to the fact that several terms are not strict, a search expression was defined not only including the broad term “no-show”, but also searching with terms such as “non-attendance” and “absenteeism”. The definition of the final search string is a result of several calibration searches realized beforehand. The detailed search string was then translated to the specific syntax of each database (see Table 2). A database search was conducted in PubMed, Scopus, Web of Science, IEEE Xplore, and ScienceDirect screening for relevant articles published between 1 January 2017 and 1 January 2022. This time span was selected to capture the most recent research from the last five years in machine learning applied to patient no-shows.

The first step in study selection was formulating eligibility criteria, which we defined in terms of desirable characteristics of the study. The list of predefined inclusion and exclusion criteria is shown in Table 3. In this work, only academic research is being considered and proposals at a commercial level are not being taken into account.

In addition to the inclusion and exclusion criteria, the studies were selected through the analysis of the (i) title; (ii) abstract and keywords; and (iii) conclusion. As a quality

**Table 2.** Search strings

Database	Search Strings
Scopus	(TITLE-ABS-KEY(no-show) OR TITLE-ABS-KEY(absenteeism)) AND TITLE-ABS-KEY("machine learning") AND (TITLE-ABS-KEY(medical) OR TITLE-ABS-KEY(healthcare)) AND (TITLE-ABS-KEY(appointment) OR TITLE-ABS-KEY(consultation))
IEEE Xplore	((("All Metadata":no-show) OR ("All Metadata":absenteeism)) AND ("All Metadata":machine learning) AND (("All Metadata":medical) OR ("All Metadata":healthcare)) AND (("All Metadata":appointment) OR ("All Metadata":consultation)))
Science Direct	("no-show"OR "absenteeism") AND ("machine learning") AND ("medical"OR "healthcare") AND ("appointment"OR "consultation")
PubMed	((no-show) OR (absenteeism)) AND ("machine learning") AND ((medical) OR (healthcare)) AND ((appointment) OR (consultation))
Web of Science	((no-show) OR (absenteeism)) AND ("machine learning") AND ((medical) OR (healthcare)) AND ((appointment) OR (consultation))

**Table 3.** Inclusion and Exclusion Criteria.

Category	Inclusion and Exclusion Criteria
Inclusion Criteria	<b>The article must:</b> Contain an abstract; Be written in English; Have been published between 1st January 2017 and 1st January 2022
Exclusion Criteria	<b>The article has a focus on:</b> Medical attendance prediction in other fields but health appointments; Medical attendance prediction without the use of machine learning techniques; Literature reviews

criterion, only works that contained substantial information were included, such as which machine learning techniques were used, which dataset attributes were available, and which algorithms and evaluation metrics were performed.

After applying the search expression in each database and subsequent initial article assessments, 63 articles were discovered. In the first stage, only the duplicated works were removed and only one version of them was kept for analysis. Most of the duplicate articles were in the Scopus database and it was decided to keep the most up-to-date article. Among these, two articles found in IEEE Xplore, seven in PubMed, and five in the ScienceDirect database were excluded from the Scopus results. An article was also removed from ScienceDirect results as it was already included in PubMed results.

In the second stage, the inclusion and exclusion criteria were applied and 24 articles were selected. The articles kept in the second stage were selected for a full reading. Table 4 shows the number of articles found and selected for each database in the respective steps mentioned.

**Table 4.** Number of articles discovered and selected in each stage.

Database	Discovered	1st Stage	2nd Stage
IEEE Xplore	3	3	3
PubMed	7	7	6
Science Direct	10	9	4
Scopus	30	15	10
Web of Science	13	2	1
<b>Total</b>	<b>63</b>	<b>36</b>	<b>24</b>

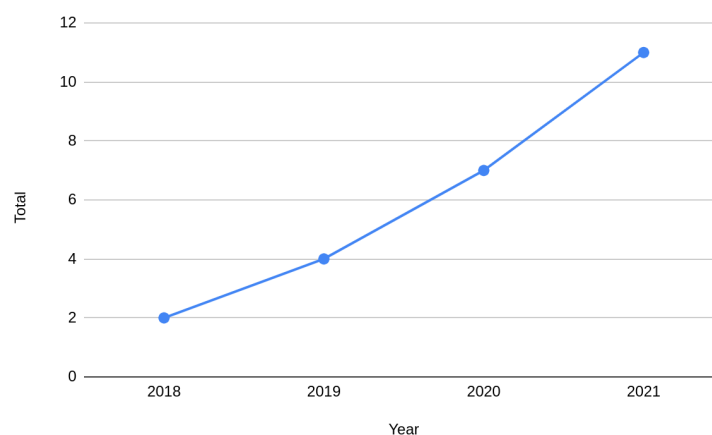
To describe the selected articles and the relations between them, as well as to develop knowledge that could not be understood by reading isolated studies, we analyzed and synthesized the data in order to extract some key information. We read the full papers ( $n = 24$ ) and documented the following information:

1. Year of publication.
2. Dataset attributes.
  - (a) Number of patients
  - (b) Number of medical appointments
  - (c) Data collection period (year)
  - (d) Country
3. No-show rate: percentage of absenteeism across the entire dataset.
4. Medical specialty: area of medicine in which the study was applied.
5. Algorithms used.
6. Selected attributes: most important predictors that influence the behavior of the model.
7. Model performance: evaluation metrics applied.

### 3. Results

Figure 1 shows the number of articles published over the years. It is noted that the number of published scientific articles referring to the no-show with the use of machine learning techniques is increasing nowadays. This fact is mainly due to the greater availability of data and the improvement of machine learning tools, such as the libraries available in different programming languages that encapsulate the complexity of implementing the algorithms.

It is worth mentioning that the problem of absenteeism in the health area has been the subject of scientific study for many years. However, most publications concern solutions focused on reducing no-shows through statistical techniques. With the advent of artificial intelligence in recent years, there was the possibility of using different machine learning techniques and optimizing solutions to mitigate no-show in medical appointments.



**Figure 1.** Number of articles published over the years.

- Q1. How much data is used to train machine learning models for no-show prediction? In total, 18 different data sets were used in the 24 studies found. Two studies [3,6] did not report the volume of data used. Only five studies used an amount of data greater than one million records, while the others used around 120 thousand records, on average. Seven works developed their solutions with the same dataset. Despite this, the works presented different approaches in the exploratory analysis of the data and in the algorithms used.

Regarding the dimensionality of the datasets, on average, 17 attributes were used to build the model in each work. The number of attributes for each work was counted based on the amount used to train the model, and not necessarily with the original attributes of the dataset. In this way, in most cases, not only the attributes of the original dataset were used, but new attributes were added through feature selection, for example.

The origin of the data was concentrated in nine different countries. Only the work by Qureshi et al. [10] did not describe the origin of the data used. Followed by the United States, Brazil was the country of origin of eight studies, seven of which used the same dataset. Regarding the data domain, that is, which context or specialty the data refer to, the vast majority concerns the primary care of patients or centers with care of multiple specialties.

With regard to the no-show rate present in the initial dataset, the highest rate observed was 85% [11]. Although this percentage represents a discrepant value compared to other works, the average absenteeism rate remained around 18% and the lowest rate was 10%. Of the 24, six works did not clearly describe the percentage of no-shows of the explored datasets. Table 5 summarizes the results in relation to the volume of data, in descending order with reference to the volume of data explored.

**Table 5.** Data Volume.

Articles	Volume	No-show Rate	No. of Features	Service	Country
[11]	33.050.363	85%	29	Primary Care	Saudi Arabia
[10]	6.000.000	-	17	Multiple Specialty	-
[12]	2.362.850	10%	12	Multiple Specialty	Spain
[13]	2.011.813	26,71%	20	Multiple Specialty	Saudi Arabia
[14]	1.087.979	11,3%	11	Multiple Specialty	Saudi Arabia
[7]	454.217	11,10%	15	Multiple Specialty	China
[5]	374.072	26%	26	Primary Care	United States
[15]	194.458	-	30	Neurology	United States
[2], [4], [16–20]	110.528	20,19%	14	Primary Care	Brazil
[21]	101.534	11,39%	-	Pediatrics	Saudi Arabia
[22]	76.285	30%	18	Family Medicine	United States
[23]	53.311	21% - 39%	7	Primary Care	Colombia
[8]	32.957	17,40%	21	Radiology	Singapore
[24]	25.523	-	16	Cardiology	United States
[25]	8.794	13,40%	14	Pediatrics	United States
[26]	4.812	-	11	Pediatrics	Brazil
[3]	-	-	9	Primary Care	United States
[6]	-	8,60%	20	Multiple Specialty	Wales

Q2. Which machine learning algorithms are used in the predictive models and which presented the best performance?

Table 6 summarizes the data found regarding the algorithms used in each work. They are presented in ascending chronological order and, for each work, the symbol “x” was inserted in the algorithms used and the symbol “o” for the algorithms used, and that obtained the best performance during the tests. The last row (“Total”) shows the number of times the algorithm was used and obtained the best performance.

In general, the works used more than one machine learning algorithm to build the model, except for work [3]. Because the present work focuses on predictive models, most of the algorithms used in the works found were for classification,

such as decision trees and logistic regression. However, regression algorithms such as linear regression and support vector regression (SVR) were also used in studies in which the objective was also to predict the number of patients who would not attend consultations in a given time window [3,25].

Table 6. Algorithms.

	AdaBoost	Artificial Neural Networks (ANN)	Bagging	Decision Tree (DT)	Deep Neural Networks (DNN)	Gradient Boosting (GB)	Gradient Boosting Machine (GBM)	General Linear Model (GLM)	Hoeffding Tree	JRip	K-Nearest Neighbors (KNN)	Linear Regression	LightGBM	Logistic Regression	Multilayer Perceptron (MLP)	Naive Bayes (NB)	Random Forest (RF)	Stochastic Gradient Descent (SGD)	Stacking	Support Vector Classifier (SVC)	Support Vector Machine (SVM)	Support Vector Regression (SVR)	XGBoost	
[24]					x												x	○						
[26]				x										x			○							
[10]	x			x		x								x	x	x	○	x			x		x	
[21]									○	○				○										
[5]	○		○	x		○								x			○							
[6]												○		x										
[7]			○	x		x					x			x			x							
[2]				○							x					x					x			
[16]	x			○																				
[17]		x				○								x			x							
[3]												○												
[18]				○										x			x							
[4]		x												x			○				x			
[13]						○								x	x		x				x			
[8]		x												x			x						○	
[25]																	x					x	○	
[23]		○												x		x								
[11]	x				○											x								
[19]						○					x			x			x							
[20]											x			x			x	○		○				
[14]									○	x														
[15]				x												x	○							
[22]		x												x			x	x	○					
[12]		x					○	x																
<b>Total</b>	<b>1</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>1</b>	<b>4</b>	<b>1</b>	<b>-</b>	<b>2</b>	<b>1</b>	<b>-</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>-</b>	<b>-</b>	<b>5</b>	<b>2</b>	<b>1</b>	<b>1</b>	<b>-</b>	<b>-</b>	<b>2</b>	

Decision trees, logistic regression, and random forest are classic algorithms that have been included in most works. Due to recent studies showing that ensemble algorithms can improve the performance of classical algorithms, some works have included them in the tests. For example, the work by Lekham et al. [5] used the bagging, AdaBoost, and gradient boosting algorithms and obtained good performance among all the candidate algorithms.

The algorithms with the best performance in the works found were gradient boosting, decision trees, and random forest. Random forest was selected as the most suitable

for building the models in most works. The performances of the algorithms of each work are presented in table 7. The metrics used in the works focus on the Area Under the ROC Curve (AUC-ROC) as it is a metric that clearly describes the results obtained from the model.

**Table 7.** Algorithms performance.

Articles	Algorithms	Performance
[24]	Stochastic Gradient Descent	0.85 (AUC-ROC)
[26]	Random Forest	0.969 (AUC-ROC)
[10]	Random Forest	0.9209 (AUC)
[21]	Logistic regression, JRip and Hoeffding Tree	0.86 (F-Score)
[5]	Random Forest, Ada Boost, Gradient Boosting and Bagging	0,73 (F-Score)
[6]	LightGBM	0.37 (F1-Score)
[7]	Bagging	0.990 (AUC)
[2]	Decision Tree	95% accuracy
[16]	Decision Tree	0.88 (AUC-ROC)
[17]	Gradient Boosting	-
[3]	Linear Regression	0.72 (AUC-ROC)
[18]	Decision Tree	78-80% accuracy
[4]	Random Forest	0.8678 (AUC-ROC)
[13]	Gradient Boosting	0.81 (AUC-ROC)
[8]	XGBoost	0.746 (AUC-ROC)
[25]	XGBoost	0.90 (AUC-ROC)
[23]	Artificial Neural Network	0.90 (AUROC)
[11]	Deep Neural Networks	0.982 (precision), 0.943 (recall)
[19]	Gradient Boosting	80.91% accuracy
[20]	Support Vector Classifier and Stochastic Gradient Descent	0.68 (AUC-ROC)
[14]	Hoeffding Tree	77.13% accuracy
[15]	Random Forest	0.68 (AUC)
[22]	Stacking	0.846 (AUC)
[12]	Gradient Boosting Machine	0.7404 (AUC-ROC)

Q3. What characteristics most influence patients not to attend a scheduled medical appointment?

The attributes of the datasets explored in the works represent the characteristics related to the patients demographics, the appointment, and the patients behavior during the appointment. Most of the works found created new attributes based on the existing ones or added new datasets, in order to have more characteristics of the problem represented through the data. The lead time attribute was created in all works, where the appointment and appointment date information was available. This attribute represents the distance from the day of appointment scheduling to the appointment day and has a considerable impact on the models.

Except for three works [11,20,25], all others consider that the most influential factors in the built model are related to the patients age, whether the patient missed a previous appointment (previous no-show), and the distance between the appointment and the patients scheduling (lead time). Other attributes, such as the geographical distance from the patients home to the clinic location, appointment date and shift, medical specialty, and whether there was prior confirmation of the appointment, had a low impact on the algorithms. Table 8 presents a summary of this information.

Table 8. Feature importance.

Articles	Patient Demographics		Appointment				Patient Behavior		
	Age	Distance	Month	Shift	Confirmation	Type	Specialty	Previous no-show (%)	Lead time
[24]								X	X
[26]			X		X				
[10]	X					X			X
[21]	X	X	X				X		
[5]	X								X
[6]	X						X		X
[7]	X	X				X			
[2]									X
[16]				X	X				X
[17]		X							X
[3]	X					X		X	
[18]	X				X				
[4]	X							X	X
[13]								X	X
[8]	X								X
[25]									
[23]			X		X				X
[11]									
[19]	X								X
[20]									
[14]							X	X	
[15]		X				X		X	X
[22]			X	X					X
[12]	X	X					X		
<b>Total</b>	<b>11</b>	<b>5</b>	<b>4</b>	<b>2</b>	<b>4</b>	<b>4</b>	<b>4</b>	<b>6</b>	<b>14</b>

Q4. What is the no-show rate reduction in medical appointments that solutions developed with the help of machine learning techniques achieve?

Only the work by Chong et. al [8] described the experiment performed in which there was a reduction in the no-show in appointments in practice. During the six months of the experiment, there was a reduction from 19.3% to 15.9% in abstentions, by sending a reminder to 25% of the patients who were pointed out by the model as at greater risk of not attending the appointment. The other works did not present metrics that demonstrate the reduction of no-shows in medical appointments, after the machine learning model development.

Four works [10,18,20,26] only presented the exploratory analysis of the data and the steps for the model building. However, they did not implement or discuss software and/or process management solutions that could be developed based on the study.

Prior communication with patients through electronic reminders, such as SMS or phone calls, was presented as a solution in most studies, as in [5–7]. In order to avoid the high cost of sending reminder notifications to every patient, some studies have proposed to optimize the sending and make them only for patients who are at high risk of no-show [2,7,16].

The study by Srinivas and Salah [24] proposes, as an alternative to reduce absenteeism in medical appointments, the subsidy for the patients transport to the health center, regarding the economic profile of the patients. Other studies [2–4] propose the use of overbooking techniques as a way of mitigating the patients non-attendance.

The optimization of appointment planning through the integration of the predictive model developed in the scheduling system [3,5,16,21], the collection of basic information for new patients through an online form [24], and the remodeling of workflow and scheduling policies [21] are alternatives mentioned in the studies as a way of reducing absenteeism.

#### 4. Discussion

The results revealed that the solutions used to mitigate medical appointments no-show with machine learning techniques do not present practical results of reducing abstentions based on the solutions presented. Except for the work by Chong et al. [8], which showed in their experiments that there was a 3.4% reduction in no-shows after the deployed solution.

Although some works have explored a dataset with a large volume of data, it was observed that the models are not directly impacted by this. The accuracy of the models developed with a smaller amount of data was higher or equivalent to the others. For example, Alshammari, Daghistani and Alshammari [11] built the model with a dataset four orders of magnitude larger in the number of records compared to [26], and the performance of the algorithms was equivalent.

The data quality is evidenced as an important factor in terms of building the machine learning models. Except for a few works, most have derived new attributes from existing ones from the original dataset or added new datasets to improve the model's comprehensiveness. Similarly, some re-balancing techniques were performed in most of the datasets in order to not bias the model training. Although the focus and objective of the research carried out and the results obtained have no focus and relationship with the treatment of patient data privacy, we use definitions, characteristics and criteria defined in these works [27],[28],[29] and [30]. These works present research and useful contributions to data privacy management in different concepts and scenarios.

The results show that the most appropriate algorithms for building the models are the decision tree algorithms, either using a binary decision tree or using ensemble methods, such as Random Forest. The work by Qureshi et al. [10] tested several more complex algorithms for building the model, such as the Multilayer Perceptron (MLP), but obtained satisfactory performance with the Random Forest algorithm. The choice of the final algorithm was also guided by the complexity of understanding the model built, such as the choice of decision trees against algorithms considered a black box, such as artificial neural networks.

#### 5. Conclusions

This work presents the state of the art regarding the use of machine learning techniques to mitigate no-show in medical appointments. The use of relevant terms and inclusion and exclusion criteria allowed the mapping of the most relevant scientific studies published. The selected works helped to identify (i) the volume of data used for training the models, (ii) which algorithms are used, (iii) which characteristics most influence the no-show behavior of patients, and (iv) which no-show reduction rate presented by the solutions found.

In fact, the relevance of the problem can be observed based on the 24 articles analyzed. This review has identified patient characteristics that were most frequently associated with no-show behavior: age of the patients, whether the patient missed a previous appointment, and the lead time between the appointment and the patients scheduling. Additionally, the results indicate that even with more complex algorithms available in artificial intelligence, decision trees algorithms are still the choice to handle the no-show in medical appointments.

Our findings shows that solutions developed with the help of machine learning techniques are still not widely integrated in scheduling systems. The majority of the surveyed studies discuss about solutions to mitigate no-shows with the help of machine

learning, but only one work has validated the experiment in a real world environment. Therefore, this study is useful for medical centers administrators interested in apply changes in their scheduling systems based on artificial intelligence solutions, and also for researchers who seek to explore literature dealing with no-show appointments and machine learning algorithms.

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