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The behaviour of patients No-Show in Online Medical Consultation System: A Systematic Literature Review

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Abstract*:* Online healthcare consultation is one of the advents in information and communication technologies (ICTs). Through this, the patient can interact with doctors and attain medical care, including information on community forums, consultations, health records, etc. Over the past few years, patients' popularity for online consultation has increased because of reduced effort. Online medical consultation provides various benefits to patients as compared with face-to-face consultation. Especially, it mitigates several problems hospitals face, such as geographical inconvenience, reduced capacity and long queues. Thus, online medical appointments and consultations highly assist the patient's self-health management. However, the patient no-shows in online appointments can directly influence the services of the healthcare sector. Different related works performed by various authors are summarised in the literature review by referring to several research papers related to the no-show prediction, risk categorisation and online consultation methodologies. A detailed description of different works is provided based on the enhancement of the balancing process to maximise the data handling efficiency and accuracy and to minimise the error rates, model complexities and training time. Also, diverse optimisation strategies are reviewed to enhance the feature selection process with better convergence and prominent feature consideration. By conducting the literature survey, the significance of techniques, the performance obtained, and the drawbacks can be analysed. Through this survey, novel methodologies can be proposed to consider the existing drawbacks to overcome with future directions.

This systematic literature review seeks to improve the thoroughness and transparency of the review process by following a method aligned with the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. In accordance with the PRISMA guidelines, this review provides a comprehensive analysis of the existing literature on the behaviour of patients No-Show in Online Medical Consultation Systems. The methodology for the review incorporates a systematic search strategy, stringent selection criteria, meticulous data extraction, and a critical analysis of the findings. The results highlight key trends, themes, and gaps in the literature, while the discussion provides insights, implications, and future research directions. In summary, employing PRISMA in this comprehensive systematic literature review enhances the validity and reliability of the findings, thereby contributing to the progression of knowledge in the domain of patient No-Show behaviour within Online Medical Consultation Systems. With the rising growth of information and communication technologies, an online appointment system is enhanced in several hospitals over the globe. However, an online outpatient appointment system faces various challenges like health, financial, scheduling, and time management problems due to a rising incidence of patient no-shows, referring to patients who do not attend their scheduled appointments. Thus, to assist the hospitals in generating proper decisions and minimise the rate of patient no-show behaviour. The performance metrics are highly utilised to prove the superiority of the machine learning models to predict no-show behaviour in online medical consultation systems.

Keywords: *Online Medical Consultation (OMC), Patient no-shows, Machine Learning Algorithms, Digital Technology, COVID-19, Behaviour of Patients*

1. Introduction

The medical industry gains societal consideration at national and international stages to a greater extent [1]. As there are spontaneous enhancements in living policies, attention towards health consciousness, the ageing population, longer life expectancy and urbanisation have increased the medical treatment demands. The demand is not restricted to treatments alone; prevention also becomes the trend. People worldwide need reliable and professional guidance every time [2], [3]. Considering the emerging demand for professional consultation, the present resource allocation for medical and health care is insufficient. The medical service imbalance is noticed, and effective allocation of medical services is the primary requirement [4]. To correct the medical resource service imbalance, the internet possesses the benefits of space constraints and breaching time through the development of online medical consultation (OMC) platforms.

The OMC proposed a novel option amongst the people to conduct consultations and health management that has been extensively adopted in recent years [5], [6]. This facility can maintain patient demand satisfaction and hospital service capacity, enhancing the socio-economic hospital benefits. Through broadband and video conferencing technologies, several people preferred online web portals to obtain an

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online consultation [7]. By utilising these technological innovations, various benefits can be achieved through online meetings in the case of both doctor and patient. The patients can assign or pick a specified general duty doctor or specialist who can be accessible over the web.

With the emergence of physician review websites and online health services, the patients can exchange opinions regarding the doctor's communication, service outlooks, complexities and extra factors of medical service procedures [8]. Through online medical consultation, the patients can generate decisions and select a suitable doctor based on the personal information from the doctor's posts, serviceability and through doctor review examination [9]. The physician reviews, including doctors' service attitude and response speed, are available on OMC platforms with considerable information. Hospitals are giving considerable attention to streamlining their operations and delivering effective medical services to patients in remote areas. This involves enhancing treatment services, improving the identification of outpatient appointments, and implementing an online appointment system based on the Internet. The increasing popularity of online appointment scheduling in outpatient clinics has led to the emergence of intricate challenges associated with patient no-show behaviour in online appointment systems [10]. The failure to attend the primary care appointment tends to disrupt the significant primary care purpose, indicating the continuous quality of care over time. The missed appointments are the key source of medical system inefficiency that may lead to deprived chronic disease control. The peculiar issue among the primary care settings is no-shows in underserved populations. A patient no-show indicates when the patient does not attend the consultation over the specified appointment period or neglects the appointment presently earlier than the particular time of doctor consultation. Because of this, the appointment time is not occupied, which in turn affects the opportunity of other patients who are in an emergency state, and tends to the sub-optimal allocation of medical resources.

Also, the no-show behaviour influenced the hospital revenue and expected performance of outpatient service, maximising the doctor's burden and working times of outpatient doctors. Simultaneously, the no-show behaviour of patients does not negatively influence the hospital organisation but also affects the healthcare scheme's financial presentation and resource usage. Understanding the factor complexity that supports over-patient prediction and non-attendance attitudes can promote personalised intervention to maximise patient engagement and efficiently utilise healthcare resources. Some of the existing research works mainly concentrate on determining connected factors over particular patient groups, including diabetes and cardiovascular diseases [11]. The non-attendance patterns for general practices are investigated by incorporating more comprehensive variables, including patient demographic, socioeconomic and practice factors.

Particularly after the outbreak of the COVID-19 pandemic, Telehealth utilisation has considerably emerged at 38× higher compared to the before-pandemic criterion as of July 2021. According to the poll conducted in the US on January 2022, 38% of patients utilise Telehealth services, which is extensively higher than before the pandemic. Patient no-shows are one of the major problems experienced by hospitals and clinics all over the globe. The rising popularity of patient no-shows for examinations and medical consultations is a major problem faced by the healthcare industry [12]. The no-shows are increased for various reasons like time conflicts, scheduling issues, hardware & software problems, secure internet connection problems, and forgetfulness factors. Also, the patient's attendance is affected by the severity of the illness, presenting complaints, comorbidities and illness history. The growing amount of appointment no-shows generates medical resource wastage, minimises the opportunity of other patients to attain the required healthcare and minimises patients' health conditions. Additionally, the no-shows affect the regular order of patient service and negatively impact the particular hospital management. To tackle this issue, several existing studies established different algorithms.

The reasons and rates for patient no-shows may vary by healthcare providers, hospitals and departments [13]. For instance, patients with specific hospitals rely mainly on information and communications technology to make medical appointments. But, they spoiled because of the environmental changes in weather [14]. The existing methods focused on minimising the number of open appointments via overbooking, utility incentives and disincentives to maintain the behaviour of patients; penalisation is introduced to fine the patients who don't attend their scheduled appointments. Moreover, the interventions are utilised to minimise the rate of no-shows with texts in short message service (SMS), phone calls and emails [15]. Because of the great advent of electronic health record technology, both predictive analytics and data mining can be used to obtain an optimal procedure for medical care decision-making.

These machine learning techniques can also predict patient no-shows effectively and support the healthcare industry by enhancing their service. To ensure accurate predictions, prediction algorithms require information such as patient age, ID, clinic neighbourhood, gender, previous medical conditions, health insurance status, and a flag indicating whether the patient received a reminder or not [16], [17]. Nowadays, advanced interventions like reminder messages and phone calls have been utilised to reduce the no-shows in the health sector. Nevertheless, such interventions are not always helpful to medical care industries in growing countries.

However, various uncertainties influence the online appointment system, leading to reduced patient satisfaction and inappropriate resource utilisation. Thus, to handle this, several researchers preferred machine learning algorithms and gained higher prediction performance because of their increased efficiency. The current studies employ various machine learning algorithms, including the Decision Tree (DT) classifier, K-Nearest Neighbor (KNN), Random Forest (RF) classifier, Logistic Regression (LR), AdaBoost (AB), and Support Vector Machine (SVM). The prediction performance improves using machine-learning algorithms; therefore, the suggested research endeavours to formulate distinct machine-learning methodologies for forecasting patient no-shows in an online appointment system.

The introduction section provides an overview of the research topic and its significance. It highlights the gaps in the existing literature and the need for a systematic review. The research objectives and research questions are clearly stated to guide the review process.

2. Materials and Methods

This section describes the comprehensive search strategy employed to identify relevant studies. It includes the databases, keywords, and inclusion/exclusion criteria used. Any limitations or challenges encountered during the search process are also addressed. The performance of the prediction model is measured by evaluating several performance metrics, and the effectiveness is proved by comparing the results with other existing techniques.

The no-show appointments indicate the non-availability of patients for treatment or the cancellation of the appointments on the same day. Because of this, revenue opportunities are missed in the healthcare system, and patient-staff satisfaction is highly decreased. Also, the causal behaviour of missing medical appointments specified over patient appointment scheduling may increase the health severity among patients.

Selection criteria outline the specific criteria used to select studies for inclusion in the review. Factors like study design, publication date, and relevance to the research topic may be taken into account when establishing inclusion criteria. A detailed explanation is provided for the study selection process, encompassing screening and eligibility assessment.

All the questions are described below:

ID	Research Question
Q1	Comparison of machine learning algorithms which is used for predicting patient's No-Show behaviour and which algorithms have the best result?
Q2	How much do machine learning-based solutions contribute to reducing the no-show rate in online medical appointments?
Q3	Benefits and barriers of predicting Model for patients No-Show behaviour in Online Medical Consultation system?

This paper describes the methodology employed in our systematic literature review. This includes the search strategy, selection criteria for including studies, data extraction process, and any statistical methods used for analysis. We ensure transparency by reporting all aspects of our review process. The author acknowledges the limitations of our systematic literature review. This may include potential biases, limitations in the search strategy, or any challenges encountered during the review process and provide a transparent assessment of the scope and generalizability of findings.

Name of Database	Number of Articles
Scopus	38
ScienceDirect	9
Springer	10
IEEE Xplore	7
NLM Database	8
Total	72

An exhaustive literature search was carried out utilizing electronic databases such as PubMed, Scopus, and Google Springer. The search procedure included relevant keywords such as "No-Show behaviour," "online medical consultation," "telemedicine," and "machine learning." The inclusion criteria for article selection were as follows: articles written in English, containing an abstract, and exploring No-Show behaviour in online medical consultations. Exclusion criteria encompassed articles of medical prediction in domains unrelated to health appointments, those not employing machine learning techniques for predicting No-Show appointments, and literature reviews.

This systematic literature review seeks to improve the thoroughness and transparency of the review process by following a method aligned with the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. In accordance with the PRISMA guidelines, this review provides a comprehensive analysis of the existing literature on the behaviour of patients No-Show in Online Medical Consultation Systems. The methodology for the review incorporates a systematic search strategy, stringent selection criteria, meticulous data extraction, and a critical analysis of the findings. The results highlight key trends, themes, and gaps in the literature, while the discussion provides insights, implications, and future research directions. In summary, employing PRISMA in this comprehensive systematic literature review enhances the validity and reliability of the findings, thereby contributing to the progression of knowledge in the domain of patient No-Show behaviour within Online Medical Consultation Systems.

To describe the selection process, illustrate below:

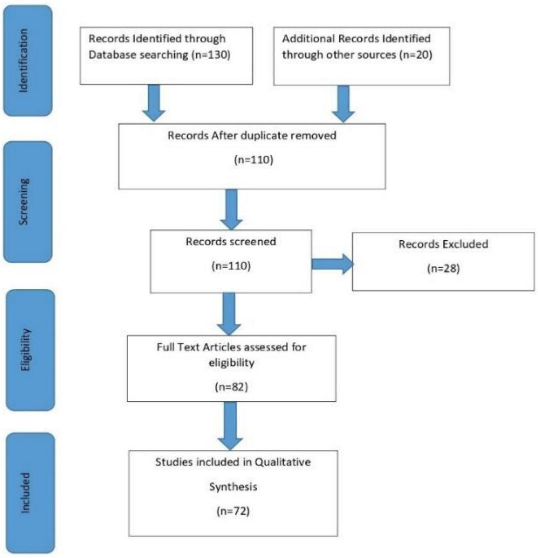

Fig 1. The Literature Selection Process

3. Result

This systematic review aims to examine the phenomenon of No-Show behaviour in online medical consultations. The review centres on articles meeting specific inclusion and exclusion criteria, published within the timeframe of 2019 to 2022. Articles must meet the inclusion criteria, which entail having an abstract, being written in English, and examining the occurrence of No-Show behaviour in online medical consultations. Articles not meeting the exclusion criteria involve those about medical prediction in domains beyond health appointments, those lacking the utilization of machine learning techniques for predicting No-Show appointments, and literature reviews. The main objective of this review is to gain insights into the factors contributing to No-Show behaviour in online medical consultations and to identify effective strategies for mitigating this issue.

This systematic review highlights the importance of understanding No-Show behaviour in online medical consultations. The included articles demonstrate the multifaceted nature of this issue and provide valuable insights into potential strategies for reducing No-Show rates. By identifying the factors associated with No-Show behaviour and leveraging machine learning techniques, healthcare providers can implement targeted interventions and improve patient engagement in online medical consultations. Further research is warranted to explore additional factors and develop more accurate predictive models to address this persistent challenge in virtual healthcare delivery.

The rapidly growing volumes of data across every industry, especially the Healthcare industry become prominent in the modern era. The crucial objective of the systematic literature review is to explore the opportunities to review theories, empirical studies, and concepts to identify the gap in online medical consultation appointments in the healthcare industry. It helps to understand and development of this research study objective. With the advancement of technology, online medical consultation has become an essential mode of communication between patients and healthcare professionals.
The survey section is conducted to analyse the efficiency, drawbacks and complexities faced in the existing models. The particular topic has been chosen by referring to specific journal papers to acquire dense knowledge regarding its significance. On the overall analysis obtained from referred journals, it is noted that there is still a huge requirement for a more efficient methodology for enhancing the prediction outcomes. The proposed work is formulated to overcome gaps that degraded the overall prediction performance. In this section, some of the valuable research is surveyed in detail.

Q. 1 Comparison of machine learning algorithms which is used for predicting patient's No-Show behaviour and which algorithms have the best result?

Comparison of Existing Algorithms Result

Publication year	Articles	Algorithms	Result
2019	[35]	JRip and Hoeffding Tree	Accuracy-76.44 (JRip) and 77.13 (Hoeffding Tree)
2019	[33]	Multi-stage prediction architecture	Accuracy-92% (Naïve bayes)
2020	[36]	SVM, random forest, LASSO regression and XGBoost	AUC-79 (Follow-up patients), 64 (Present patients)
2020	[30]	OSACI	Sensitivity-80.97 (OBL initialisation), 80.97 (OBL initialisation), 81.16 (OBL update)

2021	[23]	RF+GB+DNN	AUC-0.85, MAE-8.55, RMSE-6.88 and MAPE-12.24
2021	[21]	KNN, DT and RF+LASSO	Overall AUC-0.99
2022	[32]	SVM +RF+LR	AUC-76, F1 score-85
2022	[18]	LR+RF	AUC-0.71, F-measure-66.5%
2021	[31]	Decision Tree	Accuracy-95
2021	[37]	A11KNN and ADASYN	Better False Negative Rate Performance
2021	[25]	RF, DT and LR	Recall-0.91 and ROC-0.96
2021	[28]	DT	Recall - 99.8%
2021	[34]	JRip, Logistic regression and Hoeffding Tree	Precision, Recall- 90, F1 score-86
2021	[29]	LR, DT and tree-based ensemble classifiers	Precision-73%, recall-73.3%, F-measure-73% and accuracy-73.3%
2021	[19]	DT and AdaBoost	TPR-0.95, 0.89 (AdaBoost, DT)
2021	[20]	KNN+ ADASYN	FNR-0%
2022	[27]	NB, LR and BC	The precision of 0.85 and 0.77 was obtained for LR and NB, respectively
2022	[26]	Uncertainty-based and certainty-based prompts approach	Accuracy of 0.60, 0.55 and 0.77 was obtained for cardiology, Andrology and paediatrics, respectively
2022	[22]	Uni-variate and bi-variate chi-square test	Time-0.037s,p-value-0.05
2022	[24]	LR, RF, KNN, SVM, NN and DT	RMSE of 20.4, 18.04, 31.8, 19.13, 26.6, 20. 84 was obtained for LR, RF, KNN, SVM, NN and DT, respectively

Alabdulkarim et al. [18] define the ML framework for predicting no-shows in dental appointments. This study has three primary operations: pre-processing, feature extraction and no-show prediction. In the pre-processing stage, some of the lost data elements were removed, and outcome data were given into the feature extraction stage, where essential features were extracted. For prediction, ML-based logistic regression (LR), random forests (RF) and gradient boosting (GB) were utilised that can predict the no-shows effectively. For the hyperparameter tuning process, the grid search algorithm was utilised. The AUC of 0.71 and F-measure of 66.5% were obtained in the experimental section. However, this technique shows low training capability and is cost-effective.

Alshammari et al. [19] determined ML techniques for predicting no-show medical appointments. In this study, two ML-based algorithms, like decision tree (DT) and AdaBoost were utilised to predict the no-show medical appointments. The dataset utilised here was collected from Kaggle of 110k appointments from paediatric patients. In the experimental section, the AdaBoost and DT approach obtained the TPR of 0.95 and 0.89. However, this technique cannot be able to train for larger datasets, and the computation cost was very high.

Alaidah et al. [20] established the no-show appointments based on hybridised ML techniques. This study introduced a hybrid sampling-based k-nearest neighbour (KNN) and adaptive synthetic (ADASYN) approach to predict the no-show appointments. The dataset utilised was taken from the Medical Appointment No-Shows, having 110k appointments under specialists like hypertension, diabetes, alcoholism and handicapped. In order to discriminate against the specialist, the leading factor was also determined. The SHapley Additive exPlanation (SHAP) approach was utilised to identify the target patterns. In the experimental section, an FNR of 0% was obtained. However, this method was a complex process and required highly efficient external tools to predict the medical no-shows accurately.

Fan et al. [21] defined an ML-based approach for predicting online no-show appointments. This study utilised KNN, DT and RF to predict the online no-show appointments. To begin with, feature selection involves the application of the Least Absolute Shrinkage and Selection Operator (LASSO), ensuring accurate identification of crucial features. The dataset employed originated from an online platform of a reputable general hospital in China. In an experimental scenario, an overall AUC of 0.99 was obtained. However, this method was often subjected to high error and highly wrong predictions.

Zhao et al. [22] introduced the no-show prediction for tuberculosis patients during the COVID-19 pandemic. From the free Yale Paediatric Winchester Chest Tuberculosis Clinic, 129 patient records were utilised from 2016 to 2019. The difference between the clinical variables and no-show appointments was determined using the univariate and bi-variate chi-square test. The experimental section obtained a time of 0.037s p-value of 0.05. However, this method shows high error in finding the difference between the no-show patients for distance, language problems etc.

Srinivas and salah [23] established consultation measurement and absent prediction of the outpatient appointment using ML techniques. This study introduced three ML approaches, RF, gradient boosting and deep neural networks (DNN), for consultation measurement prediction and classification of no-show appointments. In the experimental section, the overall AUC of 0.85, MAE of 8.55, RMSE of 6.88 and MAPE of 12.24 were obtained. An online public source of about 25,523 cardiology patient records was utilised. However, this approach faces high-time complexity by utilising unwanted features extracted from the patient's record.

Rastpour and Carolyn [24] defined the no-show appointments for psychiatric outpatients using medical data. In this study, six distinct ML algorithms, namely RF, LR, Support Vector Machine (SVM), Neural Network (NN), DT, and KNN were employed. The dataset, comprising approximately eight outpatient records and encompassing 4,187 patients receiving care through 30,342 appointments, was collected from the Ontario Shores Centre of Mental Health Sciences in Canada. For tuning ML algorithms, the GS algorithm was utilised. The experimental section showed the RMSE of 20.4, 18.04, 31.8, 19.13, 26.6, 20. 84 was obtained for LR, RF, KNN, SVM, NN and DT, respectively. However, this technique does not differentiate the no-show records for males and females separately.

Salazar et al. [25] contemplated ML algorithms for predicting non-attendance patients in health care data. In this paper, three ML algorithms, LR, DT and RF, were utilised to classify the predicted outcome. Here, data pre-processing was performed, where the unwanted data was cleaned out from the medical records. Finally, the pre-processed data was given into ML algorithms in which the patient absence was classified based on gender, place, age, month etc. A dataset in real-time was obtained from the Unified Health System (SUS) at the University of Vale do Itajai in southern Brazil, consisting of nearly 5000 samples, was utilised. Of all the ML models, RF performs better with a recall of 0.91 and ROC of 0.96. However, this approach was often prone to high error in finding the difference between old and new patients due to uneven distribution.

Li et al. [26] defined the Chinese online consultation using the contextual prompts approach. In this study, two hierarchical approaches, uncertainty-based and certainty-based prompts, were utilised. These two methods mainly focus on predicting the disease using natural language prescriptions based on the patient's condition. In addition, this technique also predicts the additional information required from the patients and suggests necessary information for proper medical care. The three datasets were collected from public sources related to medicinal fields like paediatrics, Andrology and cardiology. In the experimental section, the accuracy of 0.60, 0.55 and 0.77 was obtained for cardiology, Andrology and paediatrics, respectively. However, the accuracy performance was average to increased error and also suffered from high data redundancy.

Hassija et al. [27] determined ML and blockchain (BC) based approaches for unimportant medical consultations. This study emphasised ML-based naïve Bayes (NB), and LR approaches to classify the predicted online medical consultations. In order to secure the patient's information, a BC-based secure approach was introduced. Here, some other operations like pre-processing, word2vector conversion and feature extraction eliminate unwanted details from the patient's medical records. The dataset was collected from public sources from the dialysis patient online medical records. In the experimental section, the precision of 0.85 and 0.77 was obtained for LR and NB, respectively. However, this method can be determined only for dialysis patients and not for other medical domains. In addition, the cost and time complexity was high compared to offline consultations.

Krishnan and Pushpa [28] defined the ML-based classification for no-show medical appointments. In this research, various resampling techniques, including ADAptive SYNthetic Sampling (ADASYN), Random Under Sampling (RUS), Random Oversampling (ROS), Edited Nearest Neighbor (ENN), Synthetic Minority Oversampling Technique (SMOTE), and Condensed Nearest Neighbor (CNN), were employed as a multipronged approach to balance the dataset. Finally, the DT classifier was utilised to classify the predicted no-show medical appointments. The dataset was collected from a public source of 8,000 patient records under different specialists like hypertension, diabetes, alcoholism and handicap. The overall precision achieved by the DT algorithm was about 79.7%, and recall 99.8%, respectively. However, the error was very high and we were not able to train larger datasets.

Abu et al. [29] contemplated a multi-phase predictive model for non-attendance medical appointments for outpatients in rural areas. This study undergoes three crucial stages: data analysis, evaluation of attributes and appointment status and prediction. In the data analysis, some of the patterns were given to non-attendance patients. Some ML classifiers like LR, DT and tree-based ensemble classifiers were utilised to predict the missed appointments in the medical data. A real-time dataset from the Finger Lake Community Health Centre (FLCH) in New York was utilised for the analysis process. In the experimental section, a precision of 73%, recall of 73.3%, F-measure of 73% and accuracy of 73.3% were obtained. However, this approach shows average performance due to the lack of computational resources for the tuning process. In addition, this study faces high overfitting issues due to high data redundancy.

Taking into account the impacts of healthcare systems, Aladeemy et al. [30] introduced wrapper-based methodologies rooted in three distinct variants of the Opposition-based Self Adaptive Cohort Intelligence (OSACI) procedure. The OSACI strategies presented encompassed OBL initialization, OBL update, and OBL initialization-update. These variants were derived through the integration of Self Adaptive Cohort Intelligence (SACI) with three distinct Opposition-based Learning (OBL) policies. A sensitivity rate of 80.97% was obtained in the case of OBL initialisation and OBL update, whereas 81.16% was attained in the case of OBL initialisation update. Only less number of features were considered, so effective performances cannot be obtained.

Batool et al. [31] presented research for providing a clarification that overcomes the general occurrence of medical no-shows through the creation of the ML approach. Here the existing patient datasets were used to analyse the patterns, relationship between several patient variables and missing appointment tendency. To establish the solution predictive model, a decision tree-based classification algorithm was presented. The scheduling system was designed in which the entire model analyses the missing appointment details with a 95% of accuracy rate, whereas the risk states can also be analysed. The training and testing accuracy were degraded due to the utilisation of massive datasets.

Sotudian et al. [32] presented ML models for the prediction of missed imaging appointments. This research established a parsimonious model through the recursive elimination of features. The linear and non-linear models, including Support vector machine, random forest and logistic regression, were adopted for missing imaging appointment prediction. On evaluating the performance, the non-linear random forest attained the highest AUC outcome of 76%, and an F1 score value of 85% was obtained. The proposed approach in this research was less efficient, and the variables were not considered effectively.

Akshaya et al. [33] aimed to construct a prediction model for whether the appointment is not in proper order to minimise the consequences of a no-show. A multi-stage architecture was presented for accurate prediction and to handle the imbalanced property issue. The initial stage performed a dimensionality reduction approach for data compression. The second stage dealt with the imbalanced data nature, whereas in the third stage, diverse ML algorithms were built. The accuracy of logistic regression was 80%, the neural net was 79% and Naïve Bayes as 92% to the highest, but the training ability was not effective.

Moharram et al. [34] developed a precise ML model for no-show prediction at King Faisal Specialist Hospital and Research Centre in pediatric outpatient clinics. The primary aim of this study was to gain insights into the attributes of pediatric patients with a higher likelihood of missing appointments. The best prediction model was determined from three ML approaches comparison, including JRip, Logistic regression and Hoeffding tree. The F1 score was obtained to be 86%, whereas the precision and recall were obtained to be 90%. The major drawback faced here was the non-consideration of essential features.

AlMuhaideb et al. [35] presented Hoeffding trees and JRiP methods for the patient appointment classification. The chief focus of the presented model was to construct a model for individual appointment prediction through artificial intelligence models. The historic outpatient clinic scheduling electronic medical record (EMR) data over one year. The accuracy rates of 76.44% and 77.13% were obtained in the case of JRiP and Hoeffding tree algorithms. The AUC rates of 77.6% and 86.1% were attained through JRiP and Hoeffding tree models. But the no-show risks were not effectively manipulated.

Chen et al. [36] utilised the ML algorithm for patient no-show prediction based on follow-up and present pediatric ophthalmology patient visits to estimate the significant features. The models like SVM, random forest, LASSO regression and XGBoost were employed to evaluate the performance. From these classifiers, XGBoost performed well with AUC of 79%, positive predictive value (PPV) of 54% and sensitivity of 41% in the case of follow-up patients. For present patients, the AUC of 64%, PPV of 25% and 14% of sensitivity were attained. The overall prediction performance was found to be extensively low.

Alaidah et al. [37] introduced a machine-learning algorithm designed to predict the likelihood of patients attending their upcoming appointments, aiding in the optimization of appointment rescheduling. The primary goal of the proposed research is to tackle no-show concerns to minimize the false negative rate. To address the data imbalance problem in the dataset, a hybrid sampling method named A11KNN and ADASYN (Adaptive Synthetic Sampling) was utilized. Also, the leading factors influencing the no-show rates were investigated. But the model complexities were more and effective balancing could not be obtained.

Q.2 How much do machine learning-based solutions contribute to reducing the no-show rate in online medical appointments?

Only the study conducted by Chong et al. [59] reported a practical experiment that demonstrated a decrease in the no-show rate for medical appointments. Over the six-month duration of the experiment, the absence rate decreased from 19.3% to 15.9%. This reduction was achieved by sending reminders to 25% of patients identified by the model as being at a higher risk of missing their appointments. In contrast, other works did not provide metrics showcasing a decrease in no-show rates following the development of machine learning models.

Four studies [60], [66], [67], [72] concentrated on exploratory data analysis and the procedures for constructing models, yet they did not implement or discuss software or process management solutions derived from their findings. Past studies have emphasized the use of electronic reminders, such as SMS or phone calls, as a means to improve communication with patients [45], [57], [58]. To address the cost associated with sending reminders to all patients, some studies proposed optimizing reminders for high-risk patients only [45], [52], [66], [70], [71].

Srinivas and Salah [69] proposed an alternative method to decrease absenteeism by offering transportation subsidies for patients to reach health centres, taking into account the economic profiles of the patients. Additional investigations [52]–[56], [61]-[64] recommended the utilization of overbooking strategies as a way to alleviate patient non-attendance.

Research has delved into diverse strategies, encompassing the enhancement of appointment planning by integrating predictive models into scheduling systems [38]-[51], [53], [57], [65], [68] gathering fundamental information for new patients via online forms [69], and restructuring workflow and scheduling policies [68]. All these efforts are directed towards minimizing absenteeism.

Q3. Benefits and barriers of predicting Model for patients No-Show behaviour in Online Medical Consultation system?

Machine learning algorithms are the updated version of regular algorithms. Enhancing programs involves enabling them to learn autonomously from the provided data. Machine learning algorithms are typically categorized into the training and testing phases.

During the training phase, online medical consultations from the market training data are randomly selected. A comprehensive table is created, detailing the various characteristics of users engaged in online medical consultations, including factors such as the ease of connecting with doctors, courtesy and helpfulness of doctors, feelings of safety and security, perceived value for money, time given by the doctor, attention to details provided by doctors, accuracy of diagnosis, doctor not in a hurry, and overall experience (input variables). Additionally, output variables such as cost-effectiveness, seeking a second opinion, prompt medical attention, considerations of privacy, avoiding the need to save all medical reports, access to specialists, availability, comfort and convenience, time-saving, and reducing the chances of acquiring a new illness are recorded. To input this data into the machine learning algorithm, whether it be for classification or regression, the algorithm learns a model that captures the correlation between the characteristics of users engaging in online medical consultations and the reasons behind their utilization of this service.

During the testing phase, healthcare professionals conducting online consultations can assess the characteristics of potential users (test data) engaged in online medical consultations. Subsequently, they feed this data into the machine learning algorithm, utilizing the previously established model to predict users who are likely to opt for online medical consultations.

Online medical consultations offer several potential advantages, including obtaining a second opinion, time-saving measures, receiving prompt medical attention, accessing specialists, eliminating the need to store all medical reports, ensuring privacy and availability, experiencing comfort, and convenience, benefiting from cost-effectiveness and reducing the likelihood of contracting new illnesses, among other benefits.

The entire healthcare or medical industry is facing drastic change at the moment. This research work enables users to achieve new heights in their personal and professional lives. Machine learning enhances data visualisation and enables us to make data-driven decisions. This study offers a deep understanding of data mining and a machine learning technique used in the healthcare industry and lays the foundation for future usage. This work helps everyone to understand how the research process is utilised to achieve the study objectives using suitable research methodologies.

This research work has significant advantages for policymakers, governments, companies, and new start-ups across every sector, especially healthcare.

4. Discussion

The discussion section critically analyses and interprets the findings. It explores the implications of the findings concerning the research objectives and research questions. Discrepancies, contradictions, and gaps in the literature are identified and addressed. The discussion also highlights the strengths and limitations of the review.

Some of the research gaps analysed from the survey of existing methods are listed as follows:

- Low training capability because of ineffective consideration of data.
- Complexity in training huge data with the high cost of computation.
- Maximisation of error rates and degraded prediction performance.
- High-time complexity because of ineffective feature consideration.
- Increased overfitting issues due to high data redundancy.
- Less efficient due to non-consideration of significant variables.
- Ineffective manipulation of no-show risks and improper data balancing.

To overcome the above drawbacks, it is crucial to create a predictive model which is capable of evaluating the probability of the patients attending their scheduled appointments or not. In existing, several approaches are proposed to solve these issues, but they failed due to the collection of unsuitable input data, reduced efficiency, high error rates, inappropriate feature selections and reduced learning ability. Recently, machine learning algorithms have gained more attention in prediction analysis in healthcare sectors. This machine learning algorithm can attain relevant information from the given input samples and provides exact predictions. Thus, it motivates the authors to develop different machine-learning algorithms for supporting patients in online medical appointments and consultations. Through the development of the following research objectives, the above-mentioned research gaps can be overcome effectively, and the overall performance will be maximised with a minimal amount of time and complexity.

5. Conclusion

The conclusion provides a concise summary of the main findings of our systematic literature review and their implications. It emphasizes the contributions of the review to the existing body of knowledge and proposes potential avenues for future research directions.

The proposed machine learning models can robustly predict the patient no-shows from the given input medical records. An appropriate selection of prediction variables can help the prediction algorithms to attain enhanced prediction performance. By utilising powerful pre-processing techniques, the quality of input samples gets improved and can reduce the prediction time. Moreover, effective data augmentation methods can highly mitigate the class imbalance problem. The new machine learning methods and optimisation algorithms can also aid in improving prediction accuracy. The superiority of the proposed study is revealed by performing the comparison over various traditional machine learning methods. Hence from the proposed objectives, improved results in predicting patient no-shows in online medical consultations can be attained with greater accuracy.

The performance metrics are highly utilised to prove the superiority of the machine learning models to predict the no-show behaviour in online medical consultation systems.

References

[1] Mohammadi, I., Wu, H., Turkcan, A., Toscos, T., & Doebbeling, B. N. (2018). Data Analytics and Modeling for Appointment No-show in Community Health Centers. Journal of primary care & community health, 9, 2150132718811692. https://doi.org/10.1177/2150132718811692

[2] Yang, M., Jiang, J., Kiang, M., & Yuan, F. (2021). Re-Examining the Impact of Multidimensional Trust on Patients' Online Medical Consultation Service Continuance Decision. Information Systems Frontiers, 24(3), 983–1007. https://doi.org/10.1007/S10796-021-10117-9

[3] Nelson, A., Herron, D., Rees, G. et al (2019). Predicting scheduled hospital attendance with artificial intelligence. npj Digit. Med. 2, 26. https://doi.org/10.1038/s41746-019-0103-3

[4] Wang, X., Mao, Y., & Yu, Q. (2021). From conditions to strategies: Dominance implemented by Chinese doctors during online medical consultations. Journal of Pragmatics, 182, 76-85. https://doi.org/10.1016/j.pragma.2021.06.011

[5] AlMuhaideb, Sarab, Osama Alswailem, Nayef Alsubaie, Ibtihal Ferwana, and Afnan Alnajem (2019). Prediction of hospital no-show appointments through artificial intelligence algorithms. Annals of Saudi medicine 39, no. 6: 373-381.

[6] Daye, Dania, Emmanuel Carrodeguas, McKinley Glover IV, Claude Emmanuel Guerrier, H. Benjamin Harvey, and Efrén J. Flores (2018). Impact of delayed time to advanced imaging on missed appointments across different demographic and socio-economic

factors. Journal of the American College of Radiology 15, no. 5: 713-720.

[7] Vamosi, Briana E., Lauren Mikhail, Renée L. Gustin, Kathryn C. Pielage, Katelyn Reid, Meredith E. Tabangin, Mekibib Altaye et al (2021). Predicting no show in voice therapy: avoiding the missed appointment cycle. Journal of Voice 35, no. 4: 604-608.

[8] Tan, Hongying, and Mengling Yan (2020). Physician-user interaction and users' perceived service quality: evidence from Chinese mobile healthcare consultation. Information Technology & People.

[9] Mehra, Ashwin, Claire J. Hoogendoorn, Greg Haggerty, Jessica Engelthaler, Stephen Gooden, Michelle Joseph, Shannon Carroll, and Peter A (2018). Guiney. Reducing patient no-shows: An initiative at an integrated care teaching health center. Journal of Osteopathic Medicine 118, no. 2: 77-84.

[10] Harvey, H. Benjamin, Catherine Liu, Jing Ai, Cristina Jaworsky, Claude Emmanuel Guerrier, Efren Flores, and Oleg Pianykh (2017). Predicting no-shows in radiology using regression modeling of data available in the electronic medical record. Journal of the American College of Radiology 14, no. 10: 1303-1309.

[11] Wyatt, Alvin, Jabi E. Shriki, and Puneet Bhargava (2016). Dealing with no shows: a quality improvement initiative at a tertiary care Veterans Affairs Medical Center. Journal of the American College of Radiology 13, no. 6: 702-704.

[12] Wilkinson, K. Hope, Amber Brandolino, Ali McCormick, David Deshpande, Carisa Bergner, Thomas Carver, Marc De Moya, and David Milia (2022). Lost in Follow-Up: Predictors of Patient No-Shows to Clinic Follow-Up After Abdominal Injury. Journal of Surgical Research 275: 10-15.

[13] Suk, Mi Young, Bomgyeol Kim, Sang Gyu Lee, Chang Hoon You, and Tae Hyun Kim (2021). Evaluation of Patient No-Shows in a Tertiary Hospital: Focusing on Modes of Appointment-Making and Type of Appointment. International Journal of Environmental Research and Public Health 18, no. 6: 3288.

[14] Srinivas, Sharan, and Sangdo Sam Choi (2022). Designing variable-sized block appointment system under time-varying no-shows. Computers & Industrial Engineering 172: 108596.

[15] Gupta, Rohit, Cayla Roy, Valerie Du, and SreyRam Kuy (2021). Evaluating the Impact of Provider Type and Patient Diagnosis on Patient No-Shows to Vascular Clinic. WMJ: 42.

[16] Gréanne Leeftink, Gabriela Martinez, Erwin W. Hans, Mustafa Y. Sir & Kalyan S. Pasupathy (2022) Optimising the booking horizon in healthcare clinics considering no-shows and cancellations, International Journal of Production Research, 60:10, 3201-3218, DOI: 10.1080/00207543.2021.1913292

[17] Zhan, Yang, and Zheng Zhang (2022). A study on pre-charging strategy for appointment scheduling problem with no-shows. Journal of the Operational Research Society: 1-15.

[18] Alabdulkarim, Y., Almukaynizi, M., Alameer, A., Makanati, B., Althumairy, R., & Almaslukh, A. (2022). Predicting no-shows for dental appointments. PeerJ. Computer science, 8, e1147. https://doi.org/10.7717/peerj-cs.1147

[19] Alshammari, Abdulwahhab, Raed Almalki, and Riyad Alshammari (2021). Developing a Predictive Model of Predicting Appointment No-Show by Using Machine Learning Algorithms. Journal of Advances in Information Technology Vol 12, no. 3.

[20] Alaidah, Albtool, Eman Alamoudi, Dauaa Shalabi, Malak AlQahtani, Hajar Alnamshan, and Nirase Fathima Abubacker (2021). Mining and Predicting No-Show Medical Appointments: Using Hybrid Sampling Technique. In Communication and Intelligent Systems, pp. 315-333. Springer, Singapore.

[21] Fan, Guorui, Zhaohua Deng, Qing Ye, and Bin Wang (2021). Machine learning-based prediction models for patients no-show in online outpatient appointments. Data Science and Management 2: 45-52. https://doi.org/10.1016/j.dsm.2021.06.002

[22] Zhao, Angela, Nirali Butala, Casey Morgan Luc, Richard Feinn, and Thomas S. Murray (2022). Telehealth Reduces Missed Appointments in Pediatric Patients with Tuberculosis Infection. Tropical Medicine and Infectious Disease 7, no. 2: 26.

[23] Srinivas, S., & Salah, H. (2020). Consultation length and no-show prediction for improving appointment scheduling efficiency at a cardiology clinic: A data analytics approach. International Journal of Medical Informatics, 145, 104290. https://doi.org/10.1016/j.ijmedinf.2020.104290

[24] Rastpour, A., & McGregor, C. (2022). Predicting Patient Wait Times by Using Highly Deidentified Data in Mental Health Care: Enhanced Machine Learning Approach. JMIR mental health, 9(8), e38428. https://doi.org/10.2196/38428

[25] Salazar, Luiz Henrique A., Valderi R. Q. Leithardt, Wemerson Delcio Parreira, Anita M. da Rocha Fernandes, Jorge Luis Victória Barbosa, and Sérgio

Duarte Correia. (2022). Application of Machine Learning Techniques to Predict a Patient's No-Show in the Healthcare Sector. Future Internet 14, no. 1: 3. https://doi.org/10.3390/fi14010003

[26] Li, X., Peng, D. & Wang, Y (2022). Improving patient self-description in Chinese online consultation using contextual prompts. BMC Med Inform Decis Mak 22, 170. https://doi.org/10.1186/s12911-022-01909-3

[27] Hassija, V., Ratnakumar, R., Chamola, V., Agarwal, S., Mehra, A., Kanhere, S. S., & Binh, H. T. T. (2022). A machine learning and blockchain based secure and cost-effective framework for minor medical consultations. Sustainable Computing: Informatics and Systems, 35, 100651. https://doi.org/10.1016/j.suscom.2021.100651

[28] Krishnan, Ulagapriya, and Pushpa Sangar (2021). A Rebalancing Framework for Classification of Imbalanced Medical Appointment No-show Data. Journal of Data and Information Science 6, no. 1: 178-192. DOI:10.2478/jdis-2021-0011

[29] Abu Lekham, Laith, Yong Wang, Ellen Hey, Sarah S. Lam, and Mohammad T. Khasawneh (2021). A multi-stage predictive model for missed appointments at outpatient primary care settings serving rural areas. IISE Transactions on Healthcare Systems Engineering 11, no. 2: 79-94. DOI: 10.1080/24725579.2020.1858210

[30] Aladeemy, M., Adwan, L., Booth, A., Khasawneh, M. T., & Poranki, S. (2019). New feature selection methods based on opposition-based learning and self-adaptive cohort intelligence for predicting patient no-shows. Applied Soft Computing, 86, 105866. https://doi.org/10.1016/j.asoc.2019.105866

[31] Batool, Tasneem, Mostafa Abuelnoor, Omar El Boutari, Fadi Aloul, and Assim Sagahyroon (2021). Predicting hospital no-shows using machine learning. In 2020 IEEE International Conference on Internet of Things and Intelligence System (IoTaIS), pp. 142-148. IEEE 2021.

[32] Sotudian, Shahabeddin, Aaron Afran, Christina A. LeBedis, Anna F. Rives, Ioannis Ch Paschalidis, and Michael DC Fishman (2022). Social determinants of health and the prediction of missed breast imaging appointments. BMC Health Services Research 22, no. 1: 1-11.

[33] Akshaya, Sara, Andrew McCarren, and Amal Al-Rasheed (2019). Predicting no-show medical appointments using machine learning. In International Conference on Computing, pp. 211-223. Springer, Cham, 2019.

[34] Moharram, Amani, Saud Akshaya, Sara, Andrew McCarren, and Amal Al-Rasheed. "Predicting no-show medical appointments using machine learning." In International Conference on Computing, pp. 211-223. Springer, Cham, 2019.

[35] Altamimi, and Riyad Alshammari (2021). Data Analytics and Predictive Modeling for Appointments No-show at a Tertiary Care Hospital. In 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA), pp. 275-277. IEEE, 2021.

[36] AlMuhaideb, S., Alswailem, O., Alsubaie, N., Ferwana, I., & Alnajem, A. (2019). Prediction of hospital no-show appointments through artificial intelligence algorithms. Annals of Saudi Medicine, 39(6), 373-381. https://doi.org/10.5144/0256-4947.2019.373

[37] Chen, J., Goldstein, I. H., Lin, C., Chiang, M. F., & Hribar, M. R. (2020). Application of Machine Learning to Predict Patient No-Shows in an Academic Pediatric Ophthalmology Clinic. AMIA Annual Symposium Proceedings, 2020, 293-302. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8075453/

[38] Alaidah, Albtool, Eman Alamoudi, Dauaa Shalabi, Malak AlQahtani, Hajar Alnamshan, and Nirase Fathima Abubacker (2021). Mining and Predicting No-Show Medical Appointments: Using Hybrid Sampling. Communication and Intelligent Systems: Proceedings of ICCIS 2020 204: 315.

[39] Kuiper, A., De Mast, J., & Mandjes, M. (2020). The problem of appointment scheduling in outpatient clinics: A multiple case study of clinical practice. Omega, 98, 102122. https://doi.org/10.1016/j.omega.2019.102122

[40] Li, A., & Alvarez, M. B. (2022). (148) Patient Perspectives on No-Shows in Behavioral Health Settings. Journal of the Academy of Consultation-Liaison Psychiatry, 63, S185. https://doi.org/10.1016/j.jaclp.2022.10.150

[41] He, Y., Guo, X., Wu, T., & Vogel, D. (2022). The effect of interactive factors on online health consultation review deviation: An empirical investigation. International Journal of Medical Informatics, 163, 104781. https://doi.org/10.1016/j.ijmedinf.2022.104781

[42] Yang, M., Jiang, J., Cameron, A., & Liu, X. (2023). How do you cope? Online medical consultation service uncertainty, coping strategies, and subsequent payment. Electronic Commerce Research and Applications, 61, 101294.

https://doi.org/10.1016/j.elerap.2023.101294

[43] Giwa, L., Bakdash, M., & Gunderman, R. B. (2023). No-Shows: Learning to Appreciate the Patient's Perspective. Academic Radiology, 30(11), 2791-2792. https://doi.org/10.1016/j.acra.2023.07.022

[44] Mun, J. S., Parry, M. W., Tang, A., Manikowski, J. J., Crinella, C., & Mercuri, J. J. (2023). Patient "No-Show" Increases the Risk of 90-Day Complications Following Primary Total Knee Arthroplasty: A Retrospective Cohort Study of 6,776 Patients. The Journal of Arthroplasty, 38(12), 2587-2591.e2. https://doi.org/10.1016/j.arth.2023.05.089

[45] Gessner, P., Herr, J., Mills, J., & Andaya, A. (2023). No Patient Left Behind: The Importance of Nursing Presence. Nurse Leader. https://doi.org/10.1016/j.mnl.2023.09.007

[46] Aljuaid, M. A., Li, J., Lin, C., Sitwala, P., Daiker, D., Khorjekar, G., Gupta, A., & Tirada, N. (2023). Does the Combination of Phone, Email and Text-Based Reminders Improve No-show Rates for Patients in Breast Imaging? Current Problems in Diagnostic Radiology, 52(2), 125-129. https://doi.org/10.1067/j.cpradiol.2022.09.003

[47] Fan, G., Deng, Z., Ye, Q., & Wang, B. (2021). Machine learning-based prediction models for patients no-show in online outpatient appointments. Data Science and Management, 2, 45-52. https://doi.org/10.1016/j.dsm.2021.06.002

[48] Set, K. K., Bailey, J., & Kumar, G. (2022). Reduction of No-Show Rate for New Patients in a Pediatric Neurology Clinic. The Joint Commission Journal on Quality and Patient Safety, 48(12), 674-681. https://doi.org/10.1016/j.jcjq.2022.09.001

[49] Rabiee, L., Kasubhai, M., Azeez, S., Bayas, L., Lopez, R., Luongo, J., Jain, C. M., Rana, R. P. S., Garg, S., Narang, G., Wedel, N., & Maniar, P. (2022). 726: THE IMPACT OF DIGITAL NAVIGATION PATHWAYS ON NO-SHOW RATES FOR PATIENTS UNDERGOING COLONOSCOPY: A QUALITY IMPROVEMENT STUDY. Gastroenterology, 162(7), S-186-S-187. https://doi.org/10.1016/S0016-5085(22)60445-1

[50] Mun, J. S., Parry, M. W., Tang, A., Manikowski, J. J., Crinella, C., & Mercuri, J. J. (2023). Patient "No-Show" Increases the Risk of 90-Day Complications Following Primary Total Knee Arthroplasty: A Retrospective Cohort Study of 6,776 Patients. The Journal of Arthroplasty, 38(12), 2587-2591.e2. https://doi.org/10.1016/j.arth.2023.05.089

[51] Bokinskie, James; Johnson, Payton; and Mahoney, Trevor (2015). Patient No-show for Outpatient Physical Therapy: A National Survey. *UNLV Theses, Dissertations, Professional Papers, and Capstones*. 2323. http://dx.doi.org/10.34917/7537067

[52] Borges, A., Carvalho, M., Maia, M., Guimarães, M., & Carneiro, D. (2023). Predicting and explaining absenteeism risk in hospital patients before and during COVID-19. Socio-Economic Planning Sciences, 87, 101549. https://doi.org/10.1016/j.seps.2023.101549

[53] Dag, A. Z., Johnson, M., Kibis, E., Simsek, S., Cankaya, B., & Delen, D. (2023). A machine learning decision support system for determining the primary factors impacting cancer survival and their temporal effect. Healthcare Analytics, 4, 100263. https://doi.org/10.1016/j.health.2023.100263

[54] Nasir, M., Summerfield, N., Dag, A. et al. (2020). A service analytic approach to studying patient no-shows. Serv Bus 14, 287–313. https://doi.org/10.1007/s11628-020-00415-8

[55] Joseph et al. (2022). Machine Learning for Prediction of Clinical Appointment No-Shows. International Journal of Mathematical Engineering and Management Sciences 7(4):558-574 DOI: 10.33889/IJMEMS.2022.7.4.036

[56] Deina, C., Fogliatto, F.S., da Silveira, G.J.C. et al. (2024). Decision analysis framework for predicting no-shows to appointments using machine learning algorithms. BMC Health Serv Res 24, 37. https://doi.org/10.1186/s12913-023-10418-6

[57] Laith Abu Lekham, Yong Wang, Ellen Hey, Sarah S. Lam & Mohammad T. Khasawneh (2021) A Multi-Stage predictive model for missed appointments at outpatient primary care settings serving rural areas, IISE Transactions on Healthcare Systems Engineering, 11:2, 79-94, DOI: 10.1080/24725579.2020.1858210

[58] Incze, E., Holborn, P., Higgs, G., & Ware, A. (2020). Using machine learning tools to investigate factors associated with trends in 'no-shows' in outpatient appointments. Health & Place, 67, 102496. https://doi.org/10.1016/j.healthplace.2020.102496

[59] Le Roy Chong1 Koh Tzan Tsai Lee Lian Lee Seck Guan Foo Piek Chim Chang (2020). Artificial Intelligence Predictive Analytics in the Management of Outpatient MRI Appointment No-Shows. American Journal of Roentgenology. doi.org/10.2214/AJR.19.22594

[60] Methods In Medicine C. A. M. (2023). Retracted: Efficient Prediction of Missed Clinical Appointment Using Machine Learning. Computational and mathematical methods in medicine, 2023, 9795312. https://doi.org/10.1155/2023/9795312

[61] Han, Y., Johnson, M. E., Shan, X., & Khasawneh, M. (2024). A multi-appointment patient scheduling system with machine learning and optimization. Decision Analytics Journal, 10, 100392. https://doi.org/10.1016/j.dajour.2023.100392

[62] Golmohammadi, D., Zhao, L., & Dreyfus, D. (2023). Using machine learning techniques to reduce uncertainty for outpatient appointment scheduling practices in outpatient clinics. Omega, 120, 102907. https://doi.org/10.1016/j.omega.2023.102907

[63] Daghistani, T., AlGhamdi, H., Alshammari, R., & AlHazme, R. H. (2020). Predictors of outpatients' no-show: Big data analytics using apache spark. Journal of Big Data, 7(1), 1-15. https://doi.org/10.1186/s40537-020-00384-9

[64] T. Batool, M. Abuelnoor, O. El Boutari, F. Aloul and A. Sagahyroon (2021). Predicting Hospital No-Shows Using Machine Learning. *2020 IEEE International Conference on Internet of Things and Intelligence System (IoTaIS)*, BALI, Indonesia, 2021, pp. 142-148, doi: 10.1109/IoTaIS50849.2021.9359692.

[65] Shour, A.R., Jones, G.L., Anguzu, R. et al. (2023). Development of an evidence-based model for predicting patient, provider, and appointment factors that influence no-shows in a rural healthcare system. BMC Health Serv Res 23, 989. https://doi.org/10.1186/s12913-023-09969-5

[66] Salazar, Luiz Henrique A., Valderi R. Q. Leithardt, Wemerson Delcio Parreira, Anita M. da Rocha Fernandes, Jorge Luis Victória Barbosa, and Sérgio Duarte Correia (2022). Application of Machine Learning Techniques to Predict a Patient's No-Show in the Healthcare Sector. *Future Internet* 14, no. 1: 3. https://doi.org/10.3390/fi14010003

[67] Salazar, Luiz Henrique Américo, Wemerson Delcio Parreira, Anita Maria da Rocha Fernandes, and Valderi Reis Quietinho Leithardt (2022). No-Show in Medical Appointments with Machine Learning Techniques: A Systematic Literature Review. *Information* 13, no. 11: 507. https://doi.org/10.3390/info13110507

[68] Mohammadi, I., Wu, H., Turkcan, A., Toscos, T., & Doebbeling, B. N. (2018). Data Analytics and Modeling for Appointment No-show in Community Health Centers. Journal of Primary Care & Community Health, 9. https://doi.org/10.1177/2150132718811692

[69] Srinivas, S., & Salah, H. (2020). Consultation length and no-show prediction for improving appointment scheduling efficiency at a cardiology clinic: A data analytics approach. International Journal of Medical Informatics, 145, 104290. https://doi.org/10.1016/j.ijmedinf.2020.104290

[70] Srinivas, S., & Ravindran, A. R. (2018). Optimizing outpatient appointment system using machine learning algorithms and scheduling rules: A prescriptive analytics framework. Expert Systems With Applications, 102, 245-261. https://doi.org/10.1016/j.eswa.2018.02.022

[71] Dunstan, J., Villena, F., Hoyos, J. et al. (2023). Predicting no-show appointments in a pediatric hospital in Chile using machine learning. Health Care Manag Sci 26, 313–329. https://doi.org/10.1007/s10729-022-09626-z

[72] L. H. Salazar, A. M. R. Fernandes, R. Dazzi, J. Raduenz, N. M. Garcia and V. R. Q. Leithardt (2020). Prediction of Attendance at Medical Appointments Based on Machine Learning. *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, Seville, Spain, 2020, pp. 1-6, doi: 10.23919/CISTI49556.2020.9140973.