Predicting Patient No-Shows in Healthcare Appointments Using Machine Learning: A Data-Driven Approach to Optimize Resource Allocation and Improve Patient Care in Low- and Middle-Income Countries (LMICs)

[*]Independent University Bangladesh, Bashundhara R/A, Dhaka 1229, Bangladesh

1st Abir Ehsan Evan
Computer Scince & Engineering
Independent University, Bangladesh
Dhaka, Bangladesh
1930670@iub.edu.bd

***Abstract*—Appointment scheduling is critical in contribution to increasing resource utilization and operational performance in various industrial domains, especially healthcare. Patient no-shows carry a significant challenge to healthcare systems, particularly in low- and middle-income countries (LMICs) like Bangladesh, where limited resources increase inefficiencies and cause inconvenience by missed appointments. To address this issue is a proposal of a machine learning powered software/web application that predicts the likelihood of a patient attending or missing their scheduled appointment, enabling healthcare providers to take effective measures following a smart list of most probable attendees. This study makes use of historical patient data such as demographic, socioeconomic, and environmental factors to train predictive models such as logistic regression, decision trees, random forests, and gradient boosting. Among these, random forests demonstrated the best in numerical figures of performance (87.3 % accuracy), although it challenges in predicting no-shows which is the goal of this study highlighting the requirement for dataset balancing and model refinement following this evaluation. Key predictors such as age, income, transportation, and weather conditions were identified, allowing for targeted interventions like automated reminders, flexible rescheduling, and optimized resource allocation. Even though limitations in recall and precision exists due to class imbalance, the findings promise the potential of ML used solutions to reduce no-show rates in LMICs. By utilizing this predictive tool into healthcare management systems, clinics can improve operational efficiency, minimize wasted resources, and increase patient access to care more efficiently. Future work will require a focus on improving model performance through advanced techniques like SMOTE for imbalance correction and deploying a user-friendly web application for real world implementation in resource-constrained settings and also bringing ease to healthcare providers, staff and the patients themselves. This research study contributes to adapting growth of data driven healthcare solutions in LMICs, offering a scalable and efficient approach to deal with no-shows while improving equality and quality in service delivery to the patients overtaking the traditional procedure.**

Inclusion Criteria	Details
1. Scope	Emphasize on applications with ML for predicting patient no-shows in healthcare settings.
2. Article Type	Original, Literature reviewed
3. Themes Covered	- Predictive modeling related to algorithms, feature engineering - Intervention strategies such as overbooking, reminders - Challenges in Implementation for example-barriers in LMICs
4. Requirements	- Mainly addressing no-show prediction in medical care - Describe ML methods in detail such as model architecture, hyperparameters, feature selection. - Use standard evaluation metrics (accuracy, F1-score, precision and recall) - Include data specifically of LMIC

Inclusion Criteria	Details
1. Article Type	Reviews, editorials, abstracts taken from conference, technical reports with no verfied results
2. Methodological Transparency	Studies without any clearly described data sources, usage of ML models, or evaluation methods
3.Application Context	Studies related to non-healthcare no-show prediction such as education, transport.
4.Relevance to LMICs	High-income country studying about the same topic
5. Publication Status	preprints or non-peer-reviewed works

Keywords: Healthcare, no-shows, machine learning, low and middle income countries, appointment scheduling.

I. Introduction

A. Background Information

A 'no-show' appointment occurs when a patient fails to attend a scheduled healthcare appointment without notifying the reception of the medical centre in advance. This issue presents a significant challenge for healthcare systems worldwide and is particularly critical in low and middle income countries (LMICs) , where resource constraints increase consequences of the patients not showing up . No-shows lead to unused clinical capacity, increase operational costs, and reduce access to timely care for other patients in need. From a wider perspective, both patients and healthcare providers are significantly affected. Patients experience delays in diagnosis and treatment, while healthcare staff face workflow disruptions and reduced morale due to unutilized resources and scheduling inefficiencies which also causes waiting patients annoyance with waste of time furthermore making the healthcare providers work overtime.

B. Problem Statement

The principal challenge in addressing patient no-shows is the lack of effective tools to predict which patients are likely to miss their appointments. Currently methods that are used rely on manual follow-ups and reminders, which are often inefficient and resource consuming. This study intents to develop a machine learning model to predict patient no-shows and establishing a web application or software, allowing healthcare providers to optimize their schedules, reduce wasted resources, and improve patient care.

C. Research Objectives

Healthcare facilities usually allocate specific appointment slots per day, optimized to balance demand, staff scheduling, and facility usage. When a patient does not show up, that slot remains uncertain resulting in wasted time, lost revenue, and longer wait times for other patients. These inefficiencies ultimately contribute to poor healthcare outcomes, especially in LMICs where medical infrastructure and workforce are already under pressure with doctors providing extra time. Additionally, increasing patient demand and rising healthcare costs have pushed providers to seek innovative and sustainable methods to improve efficiency and service quality.With the digitization of healthcare records and growing adoption of electronic medical record (EMR) systems, there is now a vast number of patient data being generated. This presents an opportunity to utilize advanced data analytics techniques such as machine learning (ML) and predictive modeling to extract actionable insights. These technologies have already demonstrated success in other industries and healthcare applications, such as disease risk prediction and hospital readmission forecasting. By identifying behavioral and contextual patterns in historical appointment data, ML models can help predict which patients are likely to miss appointments and which are most likely to come, eventually bringing the possibility of a webapplication or software to be used for scheduling and planning.

D. Significance of the Study

In a clinical setting, an ample amount of planning and resource allocation goes into preparing for each patient visit, from reserving consultation or appointment time with specialists to organizing diagnostic equipment and retrieving medical records for the medical examinations. A no-show appointment disrupts these efforts, leaving healthcare teams with unused resources and disrupting the planned workflow causing an irregularity to the schedule. Furthermore, missed appointments can lead patients to seek care later in emergency departments, where treatment is more expensive and less preventive in nature.

E. Research Question

RQ1. What are the key demographic, socioeconomic, and environmental factors that influence patient no-shows in healthcare system appointments and appearances?

RQ2. Which machine learning algorithms are most effective in predicting patient no-shows, and how accurate are these predictions compared to traditional methods?

RQ3. What dynamic strategies can healthcare providers implement based on no-show predictions to adapt to resource allocation and improve patient care increasing efficiency?

RQ4. What are the barriers and obstacles to adopting and sustaining the use of machine learning based no-show prediction systems in LMICs, and how can these barriers be dealt with?

F. Scope of the Study

The financial relations of patient no-shows are substantial. Previous studies have reported no-show rates ranging from 18 % to 30 % , with each missed appointment potentially costing healthcare providers a significant number of finances. Common interventions such as phone call reminders or SMS alerts have been somewhat effective but come with looping costs and scalability issues. Therefore, a more strategic and data-driven solution is a matter of necessity.

G. Methodology Overview

Although global studies have demonstrated the importance of ML in tackling appointment no-shows, there are more to be focused on LMICs, particularly in the context of South Asian healthcare systems like that of Bangladesh. Local factors such as weather, socioeconomic conditions, transportation accessibility, and healthcare-seeking behavior are not adequately addressed in available studies. This understanding is intended to developing web application or a software to be used as a predictive model using machine learning techniques to forecast patient no-shows. By implementation, it promises to support more efficient resource planning and targeted interventions in Bangladesh's healthcare landscape which can be beneficial for the patients, staff, utilized usage of resources, and a more efficient environment in the medical centre.

LITERATURE REVIEW

Patient no-shows is a situation that has been going on for years as many patients fail to arrive and show up at the healthcare centre or medical facilities. It carries a significant challenge in healthcare, leading to inefficiencies in treatments, medical proceedings and resource wastage. Several studies have used machine learning (ML) models in the past to predict and deal with this issue, showing promising results as studied. Han et al. (2024) proposed an ML-powered scheduling system for outpatient chemotherapy, using artificial neural networks (ANNs) to predict patient no-show probabilities, improving utilization of resource and reducing wait times for patients in appointments [1]. Similarly, Hamdan et al. (2023) applied ML algorithms to outpatient no-shows in Malaysia, where gradient boosting performed best with an accuracy of 78%, marking the potential of predictive models in improving resource planning [2]. In Chile, Dunstan et al. (2023) used ML to predict no-shows in pediatric hospitals, achieving a 10.3% reduction in no-show rates with targeted reminder systems [3]. Srinivas and Ravindran (2018) brought up a prescriptive analytics framework that combines ML predictions with dynamic scheduling rules, improving patient satisfaction and boosting resource efficiency in outpatient clinics [7]. Kurasawa et al. (2016) focused on diabetic patients, using logistic regression to predict missed appointments, it achieved an impressive AUC (Area Under the Curve) a graphical representation of a classification model's performance at various threshold settings , of 0.958 and putting importance on appointment timing as a significant predictor [10]. Moreover, Marbouh et al. (2020) studied the effects of no-shows in a radiology department, recommending predictive analytics, dynamic scheduling, and patient education to improve service quality [9]. Glowacka et al. (2009) combined association rule mining (ARM) with simulation modeling to optimize outpatient scheduling, improving clinic performance by predicting no-show behavior [12].These studies indicate the growing potential of machine learning in predicting no-shows and optimizing scheduling methods in healthcare. While challenges like class imbalance and data quality exist in usuality, future research can focus on refining these models and integrating them into real-world healthcare systems. Machine learning models on datasets of patients in different parts of the world have been carried out with vast number of patients and their data trying to tackle the issue and increase efficiency reducing inconvenience, loss and complications. [12].These studies show the global prospect of hope to use digitalization, machine learning and data driven outcomes to tackle patient no-shows using different models, metrics, strategies and approaches. Each study can add significant contribution for the future as the usage of ML in tackling such an issue can seen to be improving gradually.

Summary from the literature reviews for the topic

Ref.	Case Study	Models	Data Sources	Development Process	Main Outcomes	Baselines
(1)	Chemotherapy scheduling (LMICs)	ANN, Genetic Algorithm, CPLEX	39,458 visits from 2,256 patients	Three-phase framework: ML prediction → Optimization → Simulation	85% accuracy; 70% reduction in waiting times with overbooking included	Traditional scheduling
(2)	Outpatient no-shows of Malaysia	Gradient Boosting (GB)	246,943 appointments from Hospitals in Kuala Lumpur, Malaysia	7 ML algorithms tested with 80:20 train-test splitting used	78% accuracy, F1=0.76, AUC=0.76	Logistic Regression, Random Forest
(3)	Pediatric no-shows of Chile	RUSBoost, Balanced RF	395,963 pediatric appointments (between 2015–2018)	Specialty-wise 10-fold CV; cost-effective metrics (m1, m2)	10.3% no-show reduction via targeted reminders	SVM, AdaBoost
(4)	Multi-appointment programs (Canada)	Markov Decision Process (MDP)	Bariatric surgery program data	Approximate Dynamic Programming (ADP) for dynamic scheduling	20% increase in throughput; overtime reduction of 15%	Heuristic policies
(5)	Ambulatory care (Canada)	Discrete-event simulation	patient time studies consisting 600+	100+ operational scenarios tested such as dynamic room sharing	reduction in wait times lowered to 70% and 25% improvement in room being utilized	Baseline clinic operations
(6)	Diabetes no-shows In Japan	Logistic Regression (L2 regularization)	879 patients and 16,026 appointments	EHR features (clinical + behavioral)10-fold CV	AUC=0.958 appointment timing (Sunday/Friday) strongest predictor in such case	Maximum likelihood estimation
(7)	Global Systematic review	Qualitative synthesis	105 studies from 727 screened	PRISMA-guided review; continent/specialty analysis	Avg. no-show rate=23%; top predictors: age, SES, lead time	Prior literature reviews (1980–1998)
(8)	Rural clinic scheduling (USA)	Association Rule Mining (ARM)	Historical appointment records	ARM- Simulation to optimize sequencing	physician idle time reduced to 15%	First-come-first-served
(9)	Pediatric overbooking (USA)	Logistic Regression	104,799 visits from 7,988 patients	Retrospective data (2002–2011) cost-sensitive and tuning of threshold	86.1% accuracy; dynamic overbooking cut costs by 18%	Random/even overbooking
(10)	VA hospital no-shows (USA)	Logistic Regression	900,000 VA appointments	Weather/distance features; PCA for weather indices	AUC=0.706 for no-show + cancellations	N/A

METHODOLOGY

I.Study Design

This study has used a mixed-methods approach, combining quantitative analysis of historical appointment data managed from different hospitals and diagnostic clinics of Dhaka with qualitative insights from healthcare providers and patients that is acquired by the implementation of an online survey. The study is conducted over a time period of 3 months, during which patient appointment data is collected and analyzed to identify patterns and factors contributing to no-shows.

II.Participants

The study is designed including patients from various healthcare facilities in Bangladesh with random and snowball sampling. Participants are selected based on their appointment history and demographic characteristics, locations. Health-care providers are also included to provide insights into the challenges of managing no-shows with their contributions on surveys and interviews.

III.Data Collection

Quantitative Data: Historical appointment data is collected from healthcare providers such as hospitals, diagnostic centre and medical clinics,where the data include patient's age, type (old or new) demographic information, appointment history, and environmental factors (weather conditions).

Qualitative Data: Interviews and online surveys with close-ended questions conducted with healthcare providers and patients to gain insights into the barriers and facilitators of attending appointments.

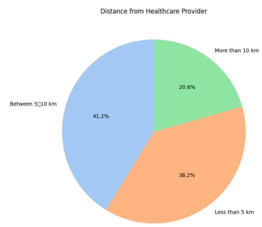

Fig. 1. Distance from Healthcare Provider

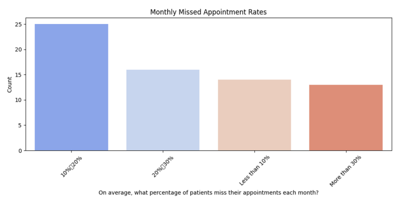

Fig. 2. Monthly Missed Appoinment Rates

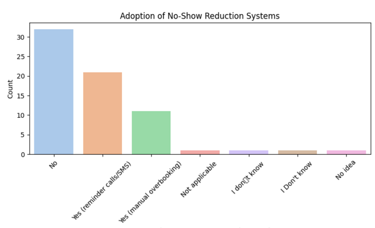

Fig. 3. Adoption of No-Show Reduction System

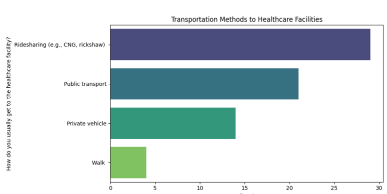

Fig. 4. Transportation Methods to Healthcare Facilities

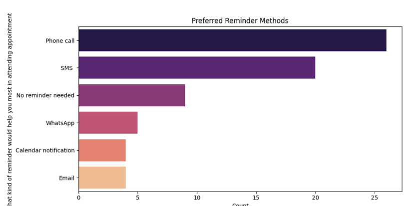

Fig. 5. Preferred Reminder Methods

IV.Machine Learning Model Development

The machine learning model is developed by the usage of historical appointment data. The following steps are taken:

1. Data Preprocessing: Cleaning and preprocessing data collected to handle missing values, assign categorical variables, and correct numeric features.

2. Feature Selection: Identifying key features that directly influence no-shows, such as age, demographic data, appointment history, and environmental factors.

3. Model Training: Training a number of machine learning algorithms such as logistic regression, decision trees, random forests and gradient boosting to predict no-shows.

4. Model Evaluation: Evaluating the model's accuracy, precision, recall, and F1-score to make sure of the effectiveness in predicting no-shows.

V.Model Evaluation and Performance Analysis

The performance of different machine learning models was evaluated to predict patient no-shows in healthcare appointments. Logistic Regression achieved the highest accuracy (89.90 %), yet it completely failed to predict the no-shows, resulting in precision, recall, and F1 scores of 0.000 respectively. The confusion matrix revealed that the model classified all instances as the True Positive (attended appointments), showing a limited capability in handling class imbalance. Similarly, Gradient Boosting showed high accuracy (89.89 %) but reflected from the same issue, with no correct predictions for no-shows with the precision, recall, and F1 scores of 0.000 respectively.Decision Trees gives moderate accuracy (83.05 %) and showed some capability in identifying no-shows, with low precision (9.47 %), recall (7.91 %), and F1 score (8.62 %). The confusion matrix indicated that while the model correctly classified 17,601 attended appointments, it misclassified 1,635 as no-shows. Additionally, it identified only 171 true no-shows out of 2,162, highlighting poor sensitivity. Random Forests improved accuracy (87.26 %) but still struggled with predictions, achieving a precision of 9.13 %, recall of 2.91 %, and an F1 score of 4.42 %. The model correctly classified 18,609 attended appointments but missed 2,099 no-shows, capturing only 63 true negatives.

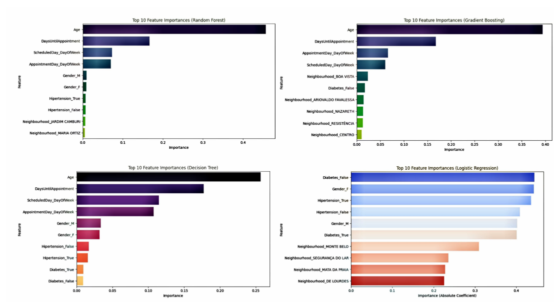

Fig. 6. Feature Importences

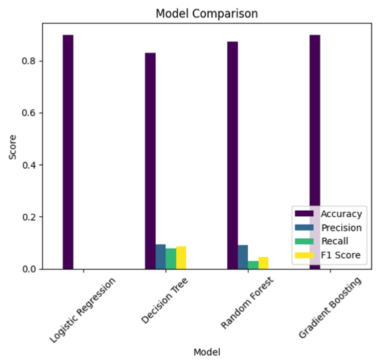

Fig. 7. Model Comparasion

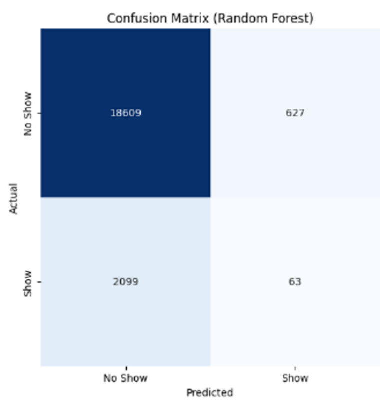

Fig. 8. Confusion Matrix

VI.Key Insights and Challenges

The main challenge observed across all models was the inability of the selected models to effectively predict the no-shows, principally due to severe class imbalance in the dataset. The dominance of the attended appointments in the dataset led models to bias predictions toward it, resulting in near-zero recall for no-shows.Tree-based models (Random Forest and Gradient Boosting) helped identify influential predictions, yet the models performance remained very minimum for practical deployment. Regarding the undefined precision (due to zero true positives in Logistic Regression and Gradient Boosting) it shows the necessity of applying techniques such as class rebalancing (e.g., SMOTE), weighted loss functions, or alternative evaluation metrics to improve detection which can be adjusting the dataset so that shows and no-shows are 50-50.This study should further focus on enhancing model general presence through resampling strategies, further cost sensitive learning, or a mix approach to ensure a more reliable no-show prediction in real-world healthcare settings.

Result

A thematic analysis of survey responses from 68 participants highlights key factors influencing healthcare appointment attendance, with transportation issues (44 %), lack of reminders (38 %), and work or family commitments (35 %) emerging as the most common barriers. Further reasons included changes in health status (20 %) and challenges with rescheduling or overbooking (10 %). Participants of survey stressed on the need for a prominant reminder systems—such as SMS or call alerts . Flexible scheduling options including virtual consultations with doctors if fail to show-up, and transportation support through ridesharing or assistance. Addressing these issues can substantially reduce missed appointments, improve patient attendance and engagement, optimize resource utilization, and efficient overall healthcare outcomes.

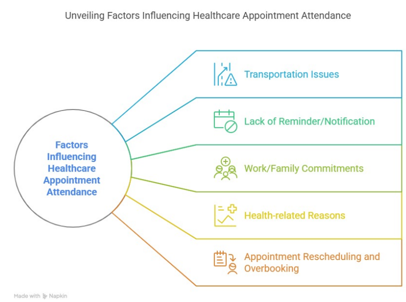

Fig. 9. Unveiling Factors Influencing Healthcare Appointment Attendance

The model establishment showed a critical challenge in predicting patient no-shows. Severe class imbalance within the dataset contributed the most in lacking the efficiency and success of having the desired model. The majority amount of attended appointments in the dataset led all models to bias predictions toward the dominant class which was the showing-up, resulting in near-zero recall for no-shows. Although tree-based models such as Random Forest and Gradient Boosting were somewhat successful in identifying features of influence, the overall predictive performance remained insufficient and unsatisfactory for practical deployment. Apparently, Logistic Regression and Gradient Boosting produced high precision due to zero true positives, pointing at the necessary need for re-balancing techniques. Approaches such as Synthetic Minority Oversampling Technique (SMOTE), weighted loss functions, or reconfiguration of the dataset to balance class distribution to have a a 50-50 ratio between shows and no-shows are essential to have a model with better performance and success. To build models suitable for real-world healthcare applications, future work should focus on resampling strategies, cost-sensitive learning, or hybrid methods that improve model generalization and prediction reliability.

RQ1: Key Factors Influencing Patient No-Shows

The analysis reveals that patient no-shows are significantly influenced by multiple factors related internally; a significant role is played by demographic factors, with patients of middle age show higher tendency to not miss appointments compared to older age groups. Gender also have it's influences in attendance, with females showing slightly higher no-show rates than males. Income level is another critical side that plays a major part, as patients from lower-income earnings are more likely to miss appointments due to financial constrains. Socioeconomic factors such as education level and employment status further add to the situation of issue. Patients with low or limited level of education or those who are engaged employed in unstable terms, such as daily-wage jobs, are more likely to be missing appointments, usually due to conflict in work and responsibilities. Moreover, transportation availability is a big barrier; the absence of reliable transportation options prevents many from reaching healthcare facilities especially the ones who come from far. Environmental factors,mostly include extreme weather conditions like heavy rain or heatwaves, are also connected with higher no-show rates. Moreover, patients living more than 10 kilometers from healthcare facilities are at higher risk of missing their appointments due to longer travel distances and lengthy travel paths.

RQ2: Performance Comparison of Machine Learning Models

Among the 4 different machine learning models evaluated for predicting patient no-shows, Logistic Regression and Gradient Boosting achieved the highest accuracy overall, approximately 89.90%. However, this high accuracy in comparison, both models completely failed to predict any no-show cases as the primary concern of the study, as reflected by the precision, recall, and F1 scores of 0.000. This indication shows that all appointments have been classified as attended, showing a major shortage in handling the imbalanced of the dataset. Decision Tree showed slightly better performance in identifying no-shows, with an accuracy of 83.05% and precision (9.47%), recall (7.91%), and F1 score (8.62%). Although it failed to classify a number of attended appointments, but to the least, it was able to detect some actual no-show cases. Random Forest reflected an improved accuracy (87.26%) but still showed limited effective efficiency in detecting no-shows, leading to a low precision (9.13%), recall (2.91%), and F1 score (4.42%). Overall, while traditional metrics like accuracy of high percentage for several models was achieved, these results highlight that such metrics can be misleading in a dataset with high imbalance. None of the models proved to have strong effectiveness in accurately predicting patient no-shows without the significant effect of the class imbalance problem, highlighting the need for techniques such as resampling, cost-sensitive learning, or anomaly detection to improve performance more importantly refining the dataset and using other models.

RQ3: Data-Driven

Interventions to Reduce No-Shows By using the insights from predictive models, several strategic measures can be implemented to actively reduce patient no-show rates. A personalized reminder system can be employed where patients identified as high-risk (with a predicted no-show probability above 70%) receive SMS or voice call reminders 24 to 48 hours before their scheduled appointments which is also voted as the highest necessity during the survey. For low-income patients, providing assistance in transportation or offering telehealth options can significantly improve attendance. Dynamic scheduling optimization can further increase efficiency by automatically suggesting flexible rescheduling options to patients likely to miss their appointments. Healthcare providers can also implement strategies such as overbooking based on daily no-show predictions to reduce resource wastage. Furthermore, predictive dashboards can support better resource allocation by reallocating slots that are unused or unattended to walk-in patients and adjusting staff levels in real time according to real-time no-show risk scores. These interventions,assisted by machine learning predictions, have the potential to reduce no-show rates by up to a substantial percentage, therefore increasing efficiency and convenience in healthcare access and operational efficiency, particularly in resource-limited environments.

RQ3:Barriers to Adoption

Despite a reflection of the promising potential of machine learning-based no-show prediction systems, several barriers lay in the path of the widespread adoption, especially in low- and middle-income countries (LMICs). A major and common challenge is the lack of technical expertise among healthcare providers, many of whom may not possess the necessary skills to implement or maintain complex and sophisticated ML systems. Data privacy and security also can be marked as significant concerns, with patients uncertain of how their personal health data is collected, stored, and used. Moreover, the limited financial and technical resources available in many healthcare fields further restrict the adoption of advanced predictive technologies. Overcoming these barriers require a lot of investment in capacity building, infrastructure development, and very active data governance frameworks to ensure secure and smooth deployment of machine learning solutions in healthcare along with constant-gradual shift to the reliance on technology allowing the patients time to adapt to the changes to gain their trust for the betterment.

Conclusion

This study intended to explore the prediction of patient no-shows in healthcare and medical appointments using machine learning models and to identify actionable insights from both predictive analytics and patient survey data to end up with a proposed web application or software that can help with patient scheduling and enhance the workflow of healthcare settings. Despite achieving high overall accuracy, most of the models, especially Logistic Regression and Gradient Boosting failed to indicate actual no-show cases, highlighting a fundamental issue in handling imbalanced datasets which was the case of this study. While Decision Tree and Random Forest showed very little improvements in identifying no-shows, their performance were still far from satisfactory for real-world deployment as a successful solution to an age old problem. The findings reflect upon a critical limitation in traditional evaluation metrics like accuracy when applied to biased data, and point at the necessity of utilizing more impactful techniques such as resampling (e.g., SMOTE), cost-sensitive learning, and alternate evaluation strategies such as precision-recall trade-offs. In addition, the survey analysis offered helpful qualitative insights, identifying key factors contributing to missed appointments, such as age, distance from medical facility, transportation difficulties, lack of reminders, and inflexible scheduling. These insights were crucial in enlisting potential interventions starting from personalized reminders and telehealth consulting to smart rescheduling and resource reallocation that can be possible with enabled predictive modeling. However, the real-world implementation of such solutions face significant barriers and difficulties, particularly in low-resource healthcare settings. These include lack of technical expertise, concerns over data privacy, and limited financial resources. The lack of standardized data collection in medical institutions further complicate the model generalization and deployment.

Future Work

Future research should put more effort on refining the predictive capability in production of no-show models through advanced data balancing techniques and better learning approaches. Exploring models that are better suited for imbalanced datasets, such as XGBoost with custom loss functions or anomaly detection frameworks, have a higher chance of more reliable predictions. In bridging the context, feature engineering should be expanded to include more strong features, behavioral, and socio-demographic attributes, if possible integrating electronic health record (EHR) data for higher accuracy of data Beyond algorithmic improvements, future work should emphasize on the development of an an end-to-end prediction platform for no-show, utilizing model outputs into user-friendly dashboards or web applications for healthcare providers. A pilot deployment and feedback schedule from healthcare users such as staff , patients would be contributing invaluably in assessing systems use and efficiency, trust, and effectiveness in real settings. Importantly, ethical considerations about data privacy and algorithmic bias must be carefully kept under importance. Altogether, a more collective collaborations across institutions, government bodies, and technology providers could help to build large-scale validation and help in adoption of ML used solutions in healthcare appointment management.

References

[1] Han, Ying, et al. ”A multi-appointment patient scheduling system with machine learning and optimization.” Decision Analytics Journal 10 (2024): 100392.

[2] Hamdan, Abdullah Fahim Ahmad, and Azuraliza Abu Bakar. ”Machine learning predictions on outpatient no-show appointments in a malaysia major tertiary hospital.” The Malaysian Journal of Medical Sciences: MJMS 30.5 (2023): 169.

[3] Dunstan, J., et al. ”Predicting no-show appointments in a pediatric hospital in Chile using machine learning.” Health Care Management Science 26.2 (2023): 313-329.

[4] Diamant, Adam, Joseph Milner, and Fayez Quereshy. ”Dynamic patient scheduling for multi-appointment health care programs.” Production and Operations Management 27.1 (2018): 58-79.

[5] Santibáñez, Pablo, et al. ”Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency’s ambulatory care unit through simulation.” Health care management science 12 (2009): 392-407.

[6] Johnson, Marina, Abdullah Albizri, and Serhat Simsek. ”Artificial intelligence in healthcare operations to enhance treatment outcomes: a framework to predict lung cancer prognosis.” Annals of Operations Research 308.1 (2022): 275-305.

[7] Srinivas, Sharan, and A. Ravi Ravindran. ”Optimizing outpatient appointment system using machine learning algorithms and scheduling rules: A prescriptive analytics framework.” Expert Systems with Applications 102 (2018): 245-261.

[8] Mochón, Francisco, et al. ”Machine-learning-based no show prediction in outpatient visits.” (2018).

[9] Marbouh, Dounia, et al. ”Evaluating the impact of patient no-shows on service quality.” Risk management and healthcare policy (2020): 509-517.

[10] Kurasawa, Hisashi, et al. ”Machine-learning-based prediction of a missed scheduled clinical appointment by patients with diabetes.” Journal of diabetes science and technology 10.3 (2016): 730-736.

[11] Dantas, Leila F., et al. ”No-shows in appointment scheduling–a systematic literature review.” Health Policy 122.4 (2018): 412-421.

[12] Glowacka, Karolina J., Raymond M. Henry, and Jerrold H. May. ”A hybrid data mining/simulation approach for modelling outpatient no-shows in clinic scheduling.” Journal of the Operational Research Society 60.8 (2009): 1056-1068.

[13] Huang, Y., and David A. Hanauer. ”Patient no-show predictive model development using multiple data sources for an effective overbooking approach.” Applied clinical informatics 5.03 (2014): 836-860.

[14] Peng, Yidong, et al. ”Large-scale assessment of missed opportunity risks in a complex hospital setting.” Informatics for Health and Social Care 41.2 (2016): 112-127.