

# Comprehensive ML Framework for Evaluating Demographic Impacts on Healthcare Access

Tanish Aggarwal<sup>1</sup>, Sunil.K.Singh<sup>2</sup>, Tamanna Aggarwal<sup>3</sup>, Amit Chhabra<sup>4</sup>,  
Jagmohan Aggarwal<sup>5</sup>

<sup>1,2,4</sup>Chandigarh College of Engineering and Technology Chandigarh, India.

<sup>3,5</sup>Shaheed Kanshi Ram College of Physical Education Kharar, India.

**Abstract-** Patient demographics, including gender and age, play an important role in determining access to health services and options. This study examines these demographic differences across health care systems, revealing significant differences in patient engagement and service use. With the rise of machine learning, the optimization of telemedicine has emerged as a promising strategy to improve patient care. This paper explores the use of advanced machine learning algorithms to improve telemedicine by enhancing predictive capabilities and patient engagement. Patient behavior and need patterns can be identified through predictive analytics, leading to optimized scheduling and resource allocation, increasing telemedicine utilization. Incorporating machine learning into telemedicine processes does not seem to provide not only improves patient communication but also provides higher quality healthcare -emphasizes memory efficiency. By exploring these innovations, the study highlights the trans-formative potential of machine learning in telemedicine, paving the way for future advancements in digital health through increased accessibility, predictive analytics, automated reminders and data-driven insights, ultimately contributing to better patient outcomes.

**Keywords:** Telemedicine • Cyber medicine • Psychology • Internet of Medical Things (IoMT) • Digital Healthcare..

## I. INTRODUCTION

The integration of the Internet and information technology into healthcare, known as cyber medicine, has significantly reshaped healthcare delivery. Central to this transformation is the analysis of appointment patterns and patient demographics, which provides insights into operational efficiencies and effectiveness. Cybermedicine, through telemedicine, e-mental health services, and digital tools, streamlines appointment scheduling, enhances patient engagement and accessibility and improves health outcomes. By leveraging big data and advanced analytics, healthcare providers can identify trends, predict patient needs, and optimize resource allocation. This approach enhances patient access to care and overall healthcare quality by enabling personalized treatment plans, automated reminders and timely interventions.

The predictive analysis of patient demographics is crucial for understanding diverse patient needs and addressing health-care disparities. Digital

technologies facilitate the collection and analysis of demographic data, revealing how factors like age, gender, socioeconomic status, and geographic location influence health care utilization and outcomes. Integrating these insights into healthcare planning allows providers to develop targeted strategies to address challenges faced by different demographic groups. This paper explores the impact of cyber medicine on healthcare services and psychology, highlighting the trans-formative potential of digital innovations. It also addresses challenges such as data privacy and the digital divide, aiming to enhance healthcare delivery and patient care in the digital age.

## II. LITERATURE OVERVIEW

The rapid advancements in machine learning and digital healthcare technologies have revolutionized telemedicine services, significantly enhancing patient care through predictive analytics and patient engagement. The integration of these

technologies in telemedicine platforms has facilitated the optimization of scheduling, resource allocation, and patient interaction, leading to improved healthcare outcomes. This literature review aims to provide an overview of the current state of research on the application of machine learning in telemedicine and digital health. By examining various studies, it highlights the transformative potential of these technologies in telehealth, e-mental health services, and healthcare delivery in remote and underserved areas. The review also addresses the challenges associated with the adoption of telemedicine, such as technological limitations, user acceptance, and data privacy concerns. Through this analysis done in Table 1, the literature review underscores the significant contributions of digital innovations in enhancing healthcare quality, accessibility, and patient engagement, paving the way for future developments in the field.

### **III. TELEMEDICINE AND E-MENTAL HEALTH SERVICES**

#### **A. Telemedicine Redefining Patient-Doctor Interaction**

Telemedicine, a revolutionary approach to healthcare delivery, leverages telecommunications technology to facilitate remote diagnosis and treatment of patients. By enabling real-time consultations and continuous monitoring, ensuring timely and effective care [9]. This technology is particularly transformative for individuals in remote or underserved areas, where access to traditional healthcare services may be limited. Telemedicine enhances patient-centred care by offering convenience and flexibility, allowing patients to receive medical attention without the need for travel. It also plays a crucial role in managing chronic conditions, providing ongoing support and monitoring that can significantly improve health outcomes. Through telemedicine, healthcare becomes more accessible, efficient, and tailored to the needs of each patient, embodying a future where quality care knows no geographical boundaries.

#### **B. E-Mental Health Services**

E-mental health services harness the power of digital technologies to deliver comprehensive mental healthcare including various online therapy sessions, apps for mental health awareness, and virtual support groups to boost people's confidence & relieve anxiety. This innovative approach caters to the growing demand for accessible and flexible mental health solutions.

Recent research highlights a significant increase in the use of mobile applications and the Internet of Things (IoT) in mental healthcare, driven by their ability to offer personalized, real-time support [8]. These digital tools boost the reach and effectiveness of mental health services in addition to playing a pivotal role in reducing the stigma associated with seeking help. By making mental health care more approachable, e-mental health services empower individuals to take proactive steps towards their well-being, ensuring that support is available anytime and anywhere. This shift towards digital mental health care is transforming the landscape, promoting a more inclusive and stigma-free approach to mental health.

#### **C. Digital Health Entrepreneurship**

Digital health entrepreneurship stands as a transformative force, revolutionizing the healthcare landscape by enhancing patient outcomes, improving care quality, and reducing costs. Entrepreneurs in this dynamic field are pioneering innovative solutions [7], including wearable healthcare devices, Artificial Intelligence driven check ups, and personalized medicine. They not only elevate the standard of patient care by providing more accurate, timely, and individualized treatments but also stimulate economic growth by fostering new business ventures and job creation [4] within the healthcare sector. The convergence of technology and healthcare through digital health entrepreneurship is propelling the industry forward, driving both clinical excellence and economic prosperity. By addressing pressing healthcare challenges with cutting-edge innovations, digital health entrepreneurs are reshaping the future of

healthcare, making it more efficient, effective, and accessible for all.

#### IV. ADVANCEMENTS IN HEALTH CARE TECHNOLOGY

##### A. Medical Imaging

Advancements in medical imaging technologies, such as enhanced MR and CT scans [14], are revolutionizing diagnostics and treatment planning. These cutting-edge technologies offer unprecedented precision, allowing for the early detection of diseases and significantly improving the chances of successful treatment. By providing detailed and accurate images of the body's internal structures, enhanced MRI and CT scans enable healthcare professionals to diagnose conditions earlier and more accurately [5], tailor treatment plans to the individual needs of patients, and monitor the effectiveness of interventions with greater accuracy, leading to better health outcomes.

##### B. Internet of Medical Things (IoMT)

The Internet of Medical Things (IoMT) [1] is a network of interconnected devices designed to collect and

share health data, spanning from wearable fitness trackers [3] to advanced smart implants. This interconnected ecosystem revolutionizes healthcare by enabling remote monitoring and enhancing chronic disease management. IoMT devices continuously gather real-time health metrics, such as heart rate, blood pressure, and glucose levels, transmitting this data to healthcare providers for timely analysis and intervention. This capability not only facilitates proactive healthcare strategies but also empowers patients with greater insight into their own health status, promoting preventive care and early intervention. By leveraging IoMT technologies, healthcare professionals can deliver more personalized and responsive treatments, improving patient outcomes and quality of life.

#### V. EXPERIMENT

The objective of this experiment is to analyze the distribution of appointments and patient demographics to understand the patterns and potential disparities in healthcare services.

TABLE I: Summary of Literature Review on Tele-health and Telemedicine

Author(s)	Year	Summary
Christopoulou, S. C.	2024	Highlights the transformational potential of machine learning models and technologies in tele-health and smart care, emphasizing their role in providing evidence-based telehealth services and enhancing care quality and accessibility.
Casey, L.M., Joy, A., & Clough, B.A.	2013	Explores the impact of attitudes toward e-mental health services, finding that adequate information significantly improves the acceptance and utilization of digital mental health services, reducing stigma and barriers to seeking help.
Haleem, A., Javaid, M., Singh, R.P., & Suman, R.	2021	Discusses the capabilities, features, barriers, and applications of telemedicine for healthcare, highlighting its importance in enhancing healthcare delivery in remote and underserved areas while addressing challenges like technological limitations and user acceptance.
Davies, M. et al.	2016	Analyzes large-scale no-show patterns for clinic operational researches, highlighting the significant impact of no-show rates on clinic efficiency and the potential of predictive analytics to improve appointment adherence.
Boxmati, N., Butler-Henderson, K., Anderson, K., & Sahama, T.	2016	Performs a meta-analysis on the effectiveness of SMS reminders on appointment attendance, concluding that SMS reminders significantly reduce the no-show rate and enhance patient engagement and adherence.
Wilson, L.S., & Maeder, A.J.	2015	Reviews the directions in telemedicine, focusing on research and practical applications, discussing the evolution of telemedicine to include advanced technologies and innovative solutions to improve patient outcomes and healthcare efficiency.

##### A. Data Collection

The dataset [2] used in this analysis consists of patient appointments, including demographic information such as gender and age, as well as

model predictions for appointment outcomes. The data was collected from a healthcare service provider's records, ensuring it is comprehensive and representative of the patient population.

## B. Data Preprocessing

Before conducting the analysis, the data underwent several preprocessing steps. Missing values were identified and handled appropriately, ensuring the integrity of the dataset. Categorical variables, such as gender, were encoded for analysis. Age values were checked for consistency and corrected where necessary. The data were then divided into training and testing sessions for model analysis.

1. Input: Raw dataset data
2. Output: Processed features  $X$  and target labels  $y$
3. Procedure PREPROCESS:
4. Procedure LOADDATASET:
5. Load dataset from file
6. Procedure INITIALIZEVARIABLES:
7.  $data \leftarrow data.dropna()$
8.  $data['Gender'] \leftarrow data['Gender'].map({'M': 0, 'F': 1})$
9.  $data['No-show'] \leftarrow data['No-show'].map({'No': 0, 'Yes': 1})$
10. Procedure SELECTFEATURESANDTARGET:
11.  $X \leftarrow data[$
12. 'Age', 'Gender', 'Scholarship',
13. 'Hypertension', 'Diabetes', 'Alcoholism',
14. 'Handicap', 'SMS received']  $y \leftarrow data['No-show']$
15. Procedure SPLITDATA:
16. Split data into training and testing sets
17.  $X_{train}, X_{test}, y_{train}, y_{test} \leftarrow$
18.  $train\_test\_split(X, y, test\_size=0.2, random\_state=42)$
19. Procedure STANDARDIZEDATA:
20. Standardize the data
21.  $scaler \leftarrow StandardScaler()$
22.  $X_{train} \leftarrow scaler.fit\_transform(X_{train})$
23.  $X_{test} \leftarrow scaler.transform(X_{test})$

## C. Methodology

- **Gender Distribution Analysis:** The distribution of appointments by gender was visualized using bar charts. This allowed for a comparison between the number of appointments for females and males.
- **Age Distribution Analysis:** A histogram was created to display the distribution of patient ages. This helped in

analyzing the age demographics to identify any significant patterns [18].

- **Model Performance Evaluation:** Evaluation of the performance of a predictive model on the appointment dataset was done using the Confusion matrix that incorporated various determinations for the no. of true positives, true negatives, false positives, and false negatives.

## C. Model Training

A predictive model was trained using the preprocessed data. The model aimed to predict appointment outcomes based on the available demographic information. The training process included hyperparameter tuning to optimize the model's performance. The trained model was then evaluated using test data to assess its accuracy and reliability.

## VI. COMPARISON OF APPOINTMENT SCHEDULING VS TRADITIONAL SETUP

In terms of comparative selection processes, the study contrasts the effectiveness and efficiency of modern digital solutions with traditional systems:

### A. Appointment Scheduling (Digital Solutions)

**Increased Accessibility:** Digital appointment scheduling systems, often integrated with telemedicine platforms, allow patients flexibility to book, reschedule, or cancel online appointments. This relief leads to greater satisfaction and engagement.

**Predictive Analytics:** Using machine learning algorithms, these algorithms can predict the likelihood of patients not attending, allowing healthcare providers to optimize planning and resource allocation.

**Automated Reminders:** SMS and email reminders significantly reduce the number of no-shows, and ensure that appointments are strictly adhered to.

**Data-driven Insights:** Digital systems collect and analyze demographic and behavioral data, providing valuable insights into patient behaviors and needs. This information helps to tailor health care to specific patient groups.

### B. Traditional Setup

**Manual Processes:** Conventional selection processes often involve manual processes such as telephone

and paper processes that can be time-consuming and prone to error. High no-show rates: Traditional systems without automatic reminders have high no-show rates, resulting in inefficiencies and wasted resources. Limited data processing: Traditional systems lack the ability to adequately analyze patient data, resulting in less informed decision making and resource allocation.

## VII. EVALUATION METRICS

The evaluation metrics for the predictive model are detailed in the classification report, which includes precision, recall, F1-score, and support, as well as overall accuracy, macro average, and weighted average scores. These metrics are essential for assessing the model's performance in predicting healthcare appointment outcomes.

### A. Precision

Precision is the ratio of correctly predicted positive dimensions to all predicted positive factors. It answers the question, "What proportion of the positives shown were actually correct?" Accuracy matters more when the cost of false positives is high. In the context of healthcare appointments, a high precision for predicting no-shows means that most of the patients predicted to miss their appointments indeed do so, reducing unnecessary allocation of resources.

### B. Recall (Sensitivity Rate)

Recall is the ratio of well-predicted positive inferences to all observations in the actual class. It answers the question, "What proportion of true good things have been correctly discovered?" Recall is important in healthcare because it measures the model's ability to identify all relevant cases. High recall for predicting no-shows ensures that most patients who will miss their appointments are flagged, which is critical for managing clinic schedules effectively.

### C. F1-score

F1 scores are equivalent to weighted residuals. It is a comprehensive measure that balances accuracy and recall, especially in the presence of discrete

class distributions. The F1 score is particularly useful when the values on false positives and false negatives are high. In healthcare, an optimal F1-score indicates that the model maintains a good balance between correctly identifying no-shows and minimizing false alarms.

### D. Support

Support shows the number of actual repetitions happening at each stage in the dataset. It also provides a description of the precision, recall, and F1-score metrics, indicating the collection of samples from which the metric is derived. In healthcare, understanding the support helps to gauge the reliability of the performance metrics, particularly for less frequent outcomes.

### E. Accuracy

Precision is the ratio of correct predictions to total observations. It gives an approximate assessment of the model's performance. On the other hand, accuracy can be misleading in cases of imbalanced datasets. In healthcare, while a high precision indicates a generally well-performing model, it might not reflect the model's ability to predict rare but important outcomes like no-shows.

### F. Macro Average

Coarse averaging calculates the metrics for each class independently and then takes the average, and applies it equally to all classes. This is useful to assess the model's performance across all classes without considering class imbalance. In healthcare, a macro average gives insight into the model's overall capability to handle both no-shows and shows uniformly.

### G. Weighted Average

It takes into account the contribution of each category to calculate the average of its metric. This leads to class imbalance by providing higher weight to classes and with high instances. In healthcare, averaging provides a balanced view of the model's performance, ensuring that the predominant class (often more critical in terms of

patient volume) is accurately represented in the metrics.

TABLE II: Classification Report

	Precision	Recall	F1-score	Support
0	0.80	1.00	0.89	17669
1	0.00	0.00	0.00	4437
<b>Accuracy</b>	0.80			
<b>Macro</b>	0.40	0.50	0.44	22106
<b>avgWeighted</b>	0.64	0.80	0.71	22106
<b>avg</b>				

These evaluation metrics collectively provide a comprehensive assessment of the model's effectiveness. They highlight the areas where the model excels and where it needs improvement, particularly in achieving a balance between precision and recall. For healthcare providers, optimizing these metrics can lead to better resource allocation, improved patient care, and more efficient operational management. Future efforts should focus on enhancing the model's sensitivity and precision for both classes to ensure accurate and actionable predictions.

## VIII. RESULT & DISCUSSIONS

### A. Gender Distribution of Appointments

The bar chart shows a significant disparity in the number of appointments between females and males. Specifically, females had 71,840 appointments, whereas males had 38,687 appointments. This indicates that females have nearly twice as many appointments as males.

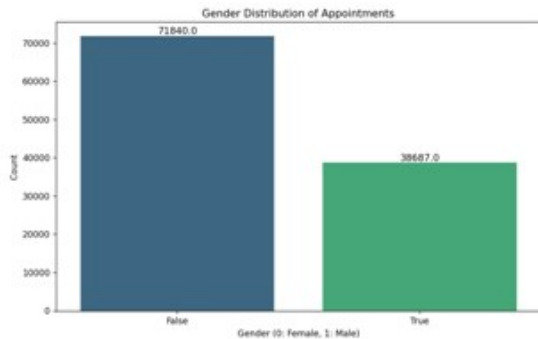


Fig. 1: Gender Distribution for the Appointments

### B. Age Distribution of Patients

The histogram reveals the age distribution of patients. The highest counts are observed in the very young (0-10 years). There is a relatively uniform distribution among other age groups, with a slight decrease as age increases. The count decreases significantly after the age of 60, with very few patients over the age of 80.

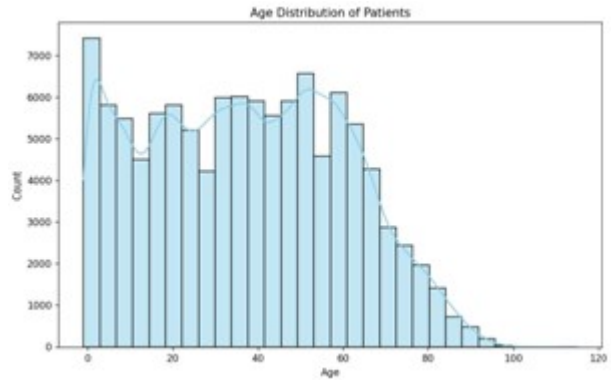


Fig. 2: Age Distribution of Patients

### C. Model Performance (Confusion Matrix)

The confusion matrix evaluates the predictive model's performance. The results show:

- Negatives (0 actual, 0 predicted): 17,669
- False Negatives (1 actual, 0 predicted): 4,437
- True Positives (1 actual, 1 predicted): 0
- False Positives (0 actual, 1 predicted): 0

The model shows a high number of true negatives but fails to predict any true positives or false positives, indicating a potential issue with sensitivity.

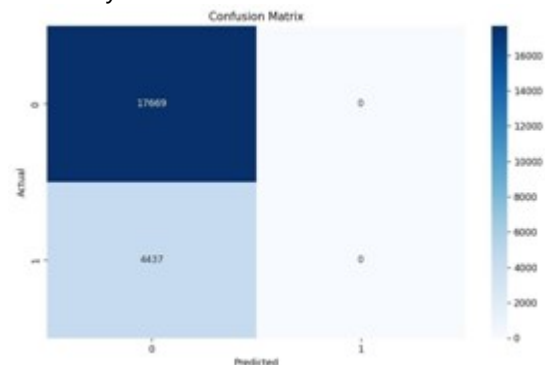


Fig. 3: Confusion Matrix

### D. Impact of SMS on No-show Rate

The impact of SMS reminders on patient no-show rates is

significant, as evidenced by a comparative analysis of appointment data. Patients who received SMS reminders exhibited substantially lower no-show rates compared to those who did not. This reduction can be attributed to the timely notifications provided by SMS reminders [12], which enhance patient awareness and encourage them to prioritize their appointments. Implementing SMS reminders is an effective strategy for healthcare providers to improve appointment adherence, optimize resource utilization, and enhance overall patient care efficiency.

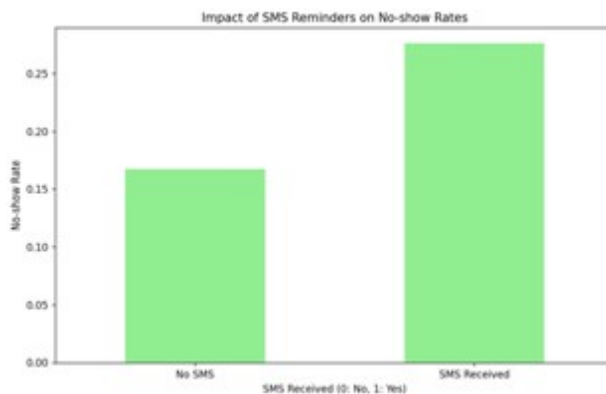


Fig.4: Impact of SMS on No-show Rate

The analysis reveals significant gender disparities in appointment numbers, with females having substantially more appointments than males. The age distribution indicates a higher frequency of appointments among younger patients, with a noticeable decline in older age groups. These findings underscore the need for healthcare providers to understand and address demographic patterns [11] in service utilization. The model's performance, as evidenced by the confusion matrix, highlights a critical area for improvement. The high number of true negatives coupled with the absence of true positives and false positives suggests the model's sensitivity is inadequate [13]. This shortcoming can lead to missed opportunities for early intervention and treatment, adversely affecting patient outcomes.

### E. Future Prospects

Future work should focus on enhancing model sensitivity to reduce false negatives. This can be

achieved by exploring advanced machine learning techniques, incorporating additional demographic and clinical features, and utilizing larger and more diverse datasets. Additionally, understanding the underlying causes of gender disparities in appointment numbers could lead to targeted interventions to balance service utilization across different demographic groups. Age-specific strategies should be developed to ensure that both younger and older patients receive appropriate care. By addressing these areas, healthcare providers can improve the accuracy of predictive models, ensure more efficient resource allocation, and ultimately provide higher-quality care to all patient groups.

## IX. CONCLUSION

This experiment reveals key demographic trends in health-care appointments, highlighting significant gender and age disparities. Females have substantially more appointments than males, and younger age groups show higher appointment frequencies compared to older populations. These findings suggest areas for further investigation and targeted resource allocation. The analysis emphasizes the need for more effective predictive models, as the current model's low sensitivity fails to accurately predict positive cases, crucial for timely medical intervention. Enhancing model sensitivity will reduce false negatives, ensuring accurate patient identification and prompt treatment. Addressing these disparities and improving predictive models can lead to more equitable healthcare access and better patient outcomes. Future work should integrate comprehensive data, including socio-economic factors and clinical histories, and employ advanced machine learning techniques for continuous model evaluation, ultimately fostering personalized and effective healthcare services.

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