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MACHINE LEARNING IN ENHANCING PATIENT ENGAGEMENT: EXPLORING HOW MACHINE LEARNING TOOLS CAN IMPROVE PATIENT ENGAGEMENT AND ADHERENCE TO TREATMENT PLANS

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Abstract

This study investigates the use of machine learning models to predict patient engagement levels in healthcare. By analyzing patient data, the study evaluates the performance of Logistic Regression, Random Forest, and Gradient Boosting models. The results show that ensemble methods, with an accuracy of 100%, outperform Logistic Regression, which has an accuracy of 98.65%. The findings highlight the potential of machine learning to enhance patient engagement and adherence to treatment plans. Implementing these models can lead to more personalized healthcare, improved patient outcomes, and optimized resource allocation.

Keywords: Patient engagement, machine learning, healthcare analytics, Logistic Regression, Random Forest, Gradient Boosting, medication adherence, predictive modeling, personalized treatment, patient adherence.

I. INTRODUCTION

Patient engagement becomes far different and quite an important facet of health care that focuses on patients' active involvement in the implementation of the treatment process. Optimizing the patient's communication is central to the compliance of the recommended treatment regime and the general wellness of the patients. The use of analytics, given the application of machine learning specificities, has potential in the application of patient engagement. These tools can also look at patient data and tell what treatment plans might be best for the patient, what schedule the patient is most likely to stick to, and what possible obstacles there are to the patient's engagement. The adaptation of machine learning in the healthcare industry is to improve the organizational framework of healthcare delivery.

Background

Patient participation is essential in getting better results from the health system and ensuring patients stick to the laid-down programs. Thus, traditional strategies have some flaws which include, difficulty in personalization and scalability [1]. Informatics uses big data to find new approaches to predict patients' behavior and their preferences. These help the involved healthcare providers to design related interference to be more specific to the users. But with network and natural language processing, machine learning can also recognize patterns that other approaches do not notice and this technology can improve the patient's dialogue with the healthcare professionals. Furthermore, it can help in the organization of chronic disease treatment, giving time and material suggestions on patients' states.

Aim and Objectives

Aim

This project aims to investigate the prospect of improving patient engagement and compliance with the treatment prescribed hence positively impacting the health care results.

Objectives

- To explore and categorize known approaches in the ML literature aimed at the improvement of patient engagement.
- To ensure that the outcomes and effects of these techniques can be compared with the level of adherence and other outcomes among the subjects.
- To compare the performance of various machine learning tools in different types of environments connected to the health care sphere.
- To explore patients' characteristics and actions affecting their level of interest and compliance.

II. LITERATURE REVIEW

2.1 Current State of Patient Engagement in Healthcare

The current forms of patient engagement in healthcare mainly include an emphasis on enhancing patient and provider interactions [2]. Patient education, self-management, and shared decision-making are some of the concepts that are well-embraced by most healthcare systems to increase patients' involvement., However, decision-making limitations; for instance, patients who are not healthcare health sectionals face difficulties in establishing proper communication. The major challenges faced by patients include poor comprehension of health information and compliance with establishing emendations provided. Moreover, there are challenges for continuity and richness in patient relationships among healthcare providers. To overcome these gaps, technological innovations such as the use of digital health, and patient portals have been developed. Nevertheless, the reported tools are not always very effective and there is continuous pressure in the field to find new solutions to engagement problems. Hence, increased interaction with patients is vital in enhancing the clients' health and ensuring find the agreed care paths.

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Fig. 2.1: Current State of Patient Engagement in Healthcare

It is important however to note that patient relations in health have changed with technological advances as well as the focus on the provision of care. Today, patient engagement is defined as a set of activities that involves different types of communication and multiple interventions allowing for patients' enhanced activation and engagement in the process of their healthcare treatment [3]. Key components of the current state include:

A. Digital Health Tools: Wearable devices and Smartphones have enhanced health metrics, medication, and information on health in the comfort of the patients. These tools enable the process of being constantly in touch and self-sustaining.
B. Telehealth and Remote Monitoring: Telemedicine and wearable health devices have increased the availability of care and enabled patients to receive continuous care without frequently visiting clinics [4]. This flexibility helps increase all sorts of conveniences and the satisfaction of patients.
C. Personalized Care Plans: There is a growing adoption of technology tools such as data analysis, and machine learning in healthcare to tailor treatment plans to the patient's characteristics. This approach promotes compliance with treatment since the strategies to be employed in treatment processes reflect the patient's wishes in the process [5].
D. Patient Portals and EHR Integration: Some of the patient portals include features that are interoperable with electronic health records or EHRs and allow patients to communicate with healthcare givers without interruption. The patient portal allows them to set an appointment, peruse their lab work and results, and even communicate conveniently with their providers.

E. Behavioral Insights and Gamification: Hype methods of behavioral science and gamification ideas are being adopted in healthcare applications and portals to engage patients. The use of rewards, cues, and other incentives and messages makes it easier for someone to stick to the treatment plan and or recommended practices [6].
F. Patient Education and Support: Education to patients on health with the provision of relevant information through the use of websites, multimedia devices, and support groups enables patients to decide on their health. It is found that educated patients are more compliant in the hospital and actively participate in the care that receives.

2.2 Role of Machine Learning in Patient Engagement

Machine Learning popularly known as ML promotes higher patient engagement with the help of unique and interactive sessions. It uses algorithms, and common patient data to make prognosis on the status of health in the population, and their respective recommendation for inputs. The utilization of WHO's predictive models allows the anticipation of the patient's requirements to be planned and foreseen ahead of time, hence effective chronic disease management [7]. NLP tools are used to analyze the patients' communication and enhance the quality of further communication and responses. Machine learning also reveals the patients' behaviour patterns to enable the provision of relevant notifications and practical information. Through EHR integration with ML tools, it is possible to enhance the care delivery process of the patients as well as the treatment plans. These make it easier for patients to adhere to prescribed treatment regimens and have their health status enhanced. Moreover, it is noted that the use of ML in engaging patients improves constantly since the recommendations are based on new data.

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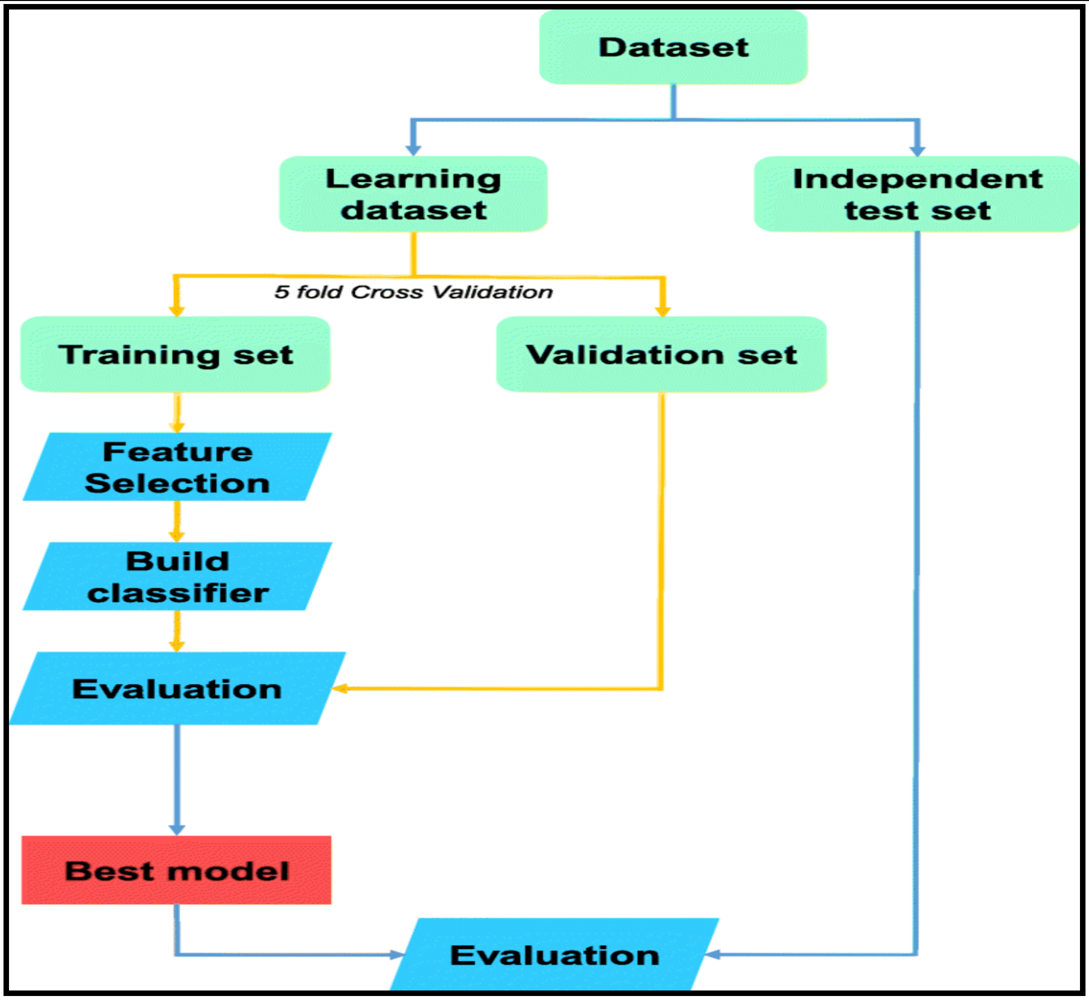

Fig. 2.2: Role of Machine Learning in Patient Engagement

That is why, the system of patient engagement is built on the fundamental basics of a sophisticated term well known under the abbreviation ML – machine learning. Here's how ML enhances patient engagement:

Personalized Treatment Plans: It encompasses the use of big data and the analysis of patients' attributes, histories, and genetic information to develop the best therapeutic approach [8]. Through patterns and outcomes analysis, relevancy ensures that treatment procedures are planned based on the overall patient needs, preferences as well as patients' general characteristics hence enhancing efficiency.

Predictive Analytics: These also provide the mechanism for the evaluation of patient prognosis depending on the data obtained in the past and present health conditions. This capability gives a chance to healthcare providers to intercede before complications and to enhance patients' compliance with prescribed treatments [9]. Predictive analytics also helps in the prevention of chronic diseases and management of chronic diseases; as a result, patients who are most likely to be worsened are quickly identified.

Behavioural Analysis and Recommendation Systems: Patients' behaviours like medication compliance and dietary habits are taken into consideration by the ML algorithms to determine the aspects likely to affect patients' engagement [10]. Recommendation systems then provide subsequent recommendations, including notifications, articles, and messages with a focus on persuasive interventions for maintenance and compliance with the set regime.
Natural Language Processing (NLP): These text analytics processes involve the assessment of large volumes of unstructured information derived from patients' discussions with care providers, social networks, and completed questionnaires [11]. This is useful in identifying patient attitudes, anxiety, and expectations thus enabling the adoption of more effective patient relation approaches that meet the patients' needs hence improving compliance.
Remote Monitoring and IoT Integration: ML algorithms work on collected data from IoT devices and wearables to supervise patient status in the home environment. There is real-time monitoring and analysis of health parameters where any deviation from normality generates an alert [12]. It entails constant listening in for the patients with feedback that enhances patient awareness and puts in place a sense of security and hence goes a long way in encouraging long-term patient self-management.

2.3 Machine Learning Models for Enhancing Patient Engagement

Automated systems are commonly used in machine learning for improving patient satisfaction involving sophisticated algorithms to forecast and impact patients' actions. Predictive analytics deals with past data to estimate the future needs of a patient or even determine a patient that requires the services of a healthcare provider. NLP models assist in the interpretation of the patient's questionnaires and responses, including the use of a chatbot or virtual assistant. Recommendation systems employ user data to recommend specific health interventions or timely reminders to enhance patients' compliance with the recommended treatment. Thus, reinforcement learning models update the course of action depending on the feedback, making the intervention methods more effective [13]. The decision tree and other methods of the ensemble type can divide the patients into certain categories of engagement to optimize interventions. Furthermore, there is the issue of clustering that divides the patients to discover similarities and engagement strategies able to address them.

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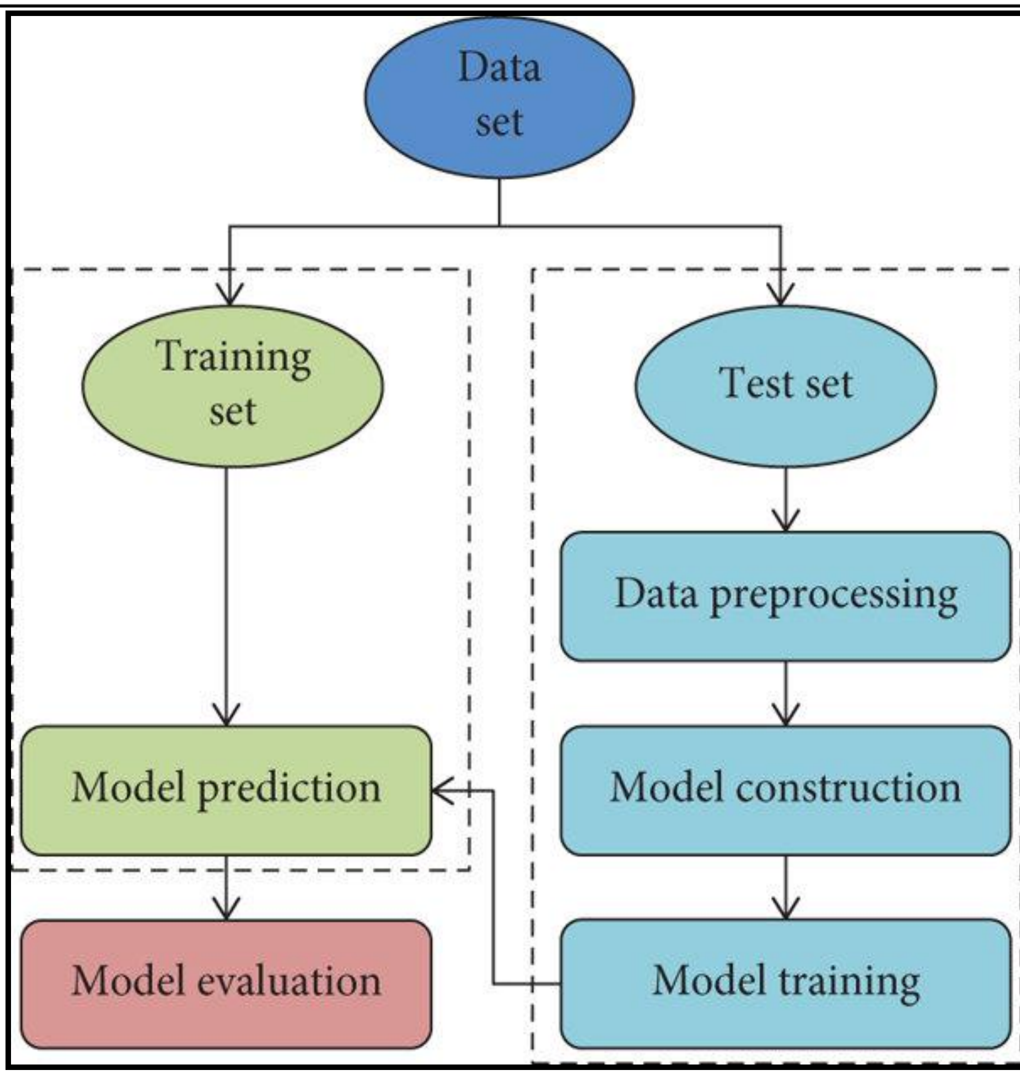

Fig. 2.3: Machine Learning Models for Enhancing Patient Engagement

Various applications of the concepts of the ML models that are useful in the enhancement of patient engagement include the following. Here are several key ML models and their applications in enhancing patient engagement:

Predictive Analytics Models: These models retrieve the patient data from the past or patients' electronic health records and forecast their future health conditions or likely complications or non-compliance to regimes [14]. Realizing the factors that could go wrong enables healthcare providers to develop specific leaner interventions aimed at enhancing the levels of patients' participation and effectiveness.

Recommendation Systems: Much like the recommendation systems applied in e-commerce, and focused on patients' records to offer personalized treatment suggestions, including medication intake prompts, changes in life routines, and preventive measures [15]. Such systems improve patient interaction with the client through the provision of appropriate recommendations based on each of the patient's fitness agendas and likes.
Natural Language Processing (NLP) Models: These NLP models are used to understand the sentiments, concerns, and level of satisfaction of patients from textual data generated from patients' and providers' discussions, social media, and feedback. This information would enable the health care providers to adopt the necessary communication strategies and intercessions to address the patient's psychological and emotional requirements.
Clustering and Segmentation Models: These models categorize the patient into groups for appropriate intervention to be offered to them based on their characteristics or behavior. Such knowledge helps providers create communication appealing to specialized patient categories, which in turn increases the latter's compliance and satisfaction [16].
Deep Learning Models for Image and Signal Processing: In the context of specialties such as radiology or cardiology, deep learning models work on a raw input form of medical images and signals from diagnostic procedures to assist in diagnosis and planning of the treatment. Due to the complexity of the assigned tasks as well as the offered precise analysis, these models help clinicians engage the patients and provide them with accurate information needed for timely appropriate treatment.

2.4 Impact on Patient Adherence and Outcomes
Thus, mobile learning tools have greatly impacted patient compliance and outcomes. Since clinical databases contain information about chronic patients, predictive models help to assess the possibility of non-adherence and outcomes necessary actions, referring to such patients. Applying experience knowledge, machines can make a prognosis when the patient is likely to be non-adherent to appointments or dosages [17]. Since these tools are used for the patient's schedule and lifestyle, the adherence rates can be enhanced by the reminders and suggestions provided. Moreover, machine learning models are used in the development of treatment plans for individual patients, which might enhance the efficacy of particular treatments in the process. Improved patient interaction by making the communication process more personalized can improve the client's compliance with the set plans. This has been known to help patients achieve better clinical outcomes, and fewer readmissions to hospital are observed.

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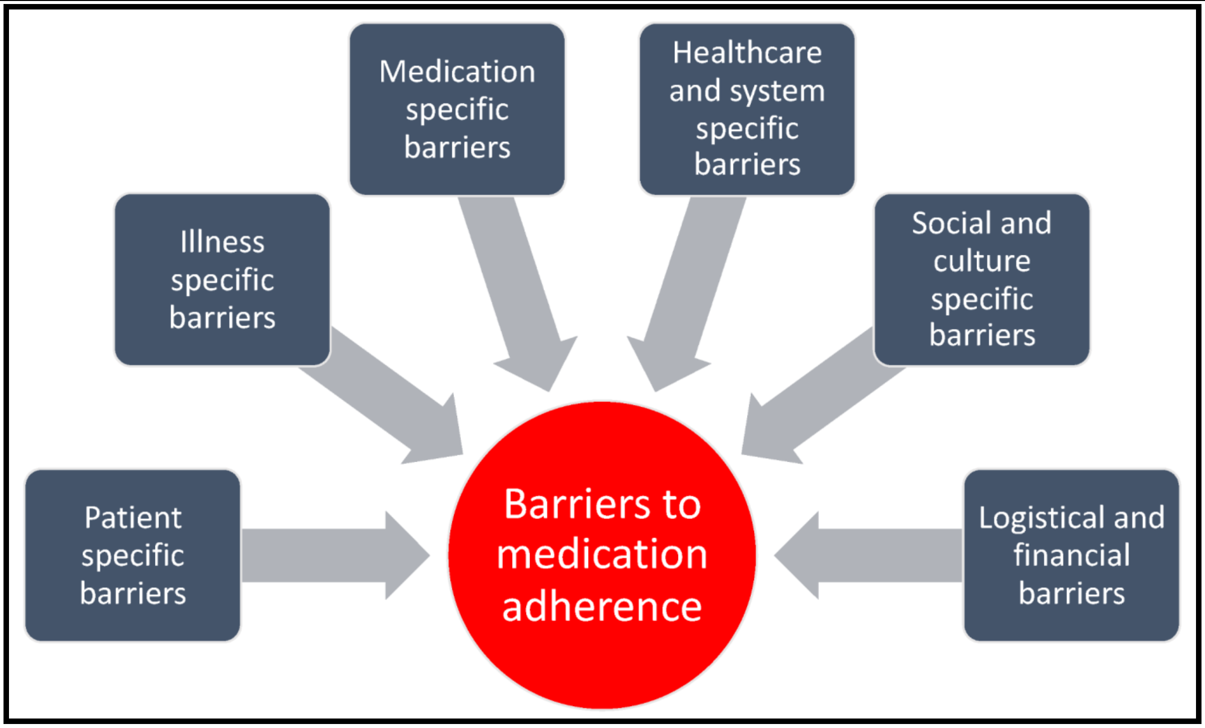

Fig. 2.4: Impact on Patient Adherence and Outcomes

Indirectly, the integration of ML in healthcare has provided highly interesting findings about patients' adherence to therapy regimens and the overall population's health status, which shift the typical paradigms of healthcare [18]. Here's how ML influences adherence and outcomes: This is how ML affects adherence and the resultant outcomes:

Personalized Treatment Plans: By employing extremely large data inputs, the ML algorithms build personalized and unsymmetrical treatment programs based on the patient's features or previous sicknesses and current state of health data [19]. Thus, medical evaluation using an algorithm from the field of ML in its integrated state with health care produces beneficial consequences in terms of increasing the relevance and efficiency of the care plans; as such plans are created based on the individual needs of the patient.

Predictive Analytics: Outcome prediction of patients is primarily conducted according to the criteria developed via ML models using the history and current state of the patient's illness. This capability enables a healthcare provider to prevent adverse effects and non-adherence before these happen within the patient's plan [20]. Such implementation enhances compliance and cessation of the events, enhancing the general health status.

Behavioural Insights and Interventions: Through the application of ML, the systems accustom themselves to patients' behavioural patterns and choices with the development of custom solutions. Another type of intervention includes responsibility prompts, counselling,

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recommendations concerning diet and exercise, and other strategies meant to increase patients' commitment and compliance with prescriptions [21]. By removing the behavioural barriers, the ML increases patients' interest and compliance with the treatment process.

Remote Monitoring and Real-time Feedback: Telemonitoring solutions that are based on the ML approach use the data collected from IoT devices and wearable technologies to assess patient's conditions permanently. Notifications of absolute and relative deviations in the vital signs allow patients and providers to make timely changes to the regimen. This way, the patients are well informed and their level of responsibility is enhanced hence leading to better compliance and results.

Enhanced Clinical Decision Support: Healthcare professionals can use the information from large volumes of medical data, through the application of ML to make better decisions [22]. The use of techniques in clinical practice can minimize the possibilities of errors while delivering treatments and can also use the patient's clinical record to effectively identify what kind of care is desirable and best suited for a patient hence enhancing the quality of health care delivery.

2.5 Literature Gap

The literature review reveals that prior research mainly investigates the efficacy of these tools regarding their short-term effectiveness without research on their long-term performance. Moreover, there is a lack of research into patients' demographics and behaviors, which affect their engagement and adherence. One major area of development is the incorporation of ML tools into the existing healthcare systems. Concerns in the area of ethics and patients' privacy as regards machine learning in the patient system arintounmet. Fillinghealthcare has been useful in giving a better picture of the possibilities and challenges of these technologies.

III. METHODOLOGY

3.1 Data Collection and Pre-processing

Data collection relates to the acquisition of information concerning a patient, and multiple sources include EHRs, surveys, and engagement record keeping. Patient data needs to be complete to let them represent populations of patients that are taken for investigation. Data pre-processing involves ensuring that inconsistencies, missing values, and outliers that are likely to affect results are eradicated [23]. This step also involves data cleaning ensuring data is normalized and transformed, to a suitable format for analysis. Variables that have the greatest impact on a patient's engagement and adherence must also be identified as feature selection is equally important.

Demand Forecasting

^=N1i=1∑Ny^i

Mean Absolute Error (MAE):

MAE=n1i=1∑n∣yi−y^i∣

Moreover, an employment of data anonymization takes place to avoid any violation of a patient's right to privacy and to adhere to ethical requirements. When data is gathered from

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multiple sources it might also be necessary to use integration techniques to ensure consistency [24]. After data pre-processing, the dataset is split into training,-validation, and test datasets for the evaluation of the performances. This process helps to filter and refine the raw data to obtain the required information about patient engagement and treatment adherence suitable for the models' training.

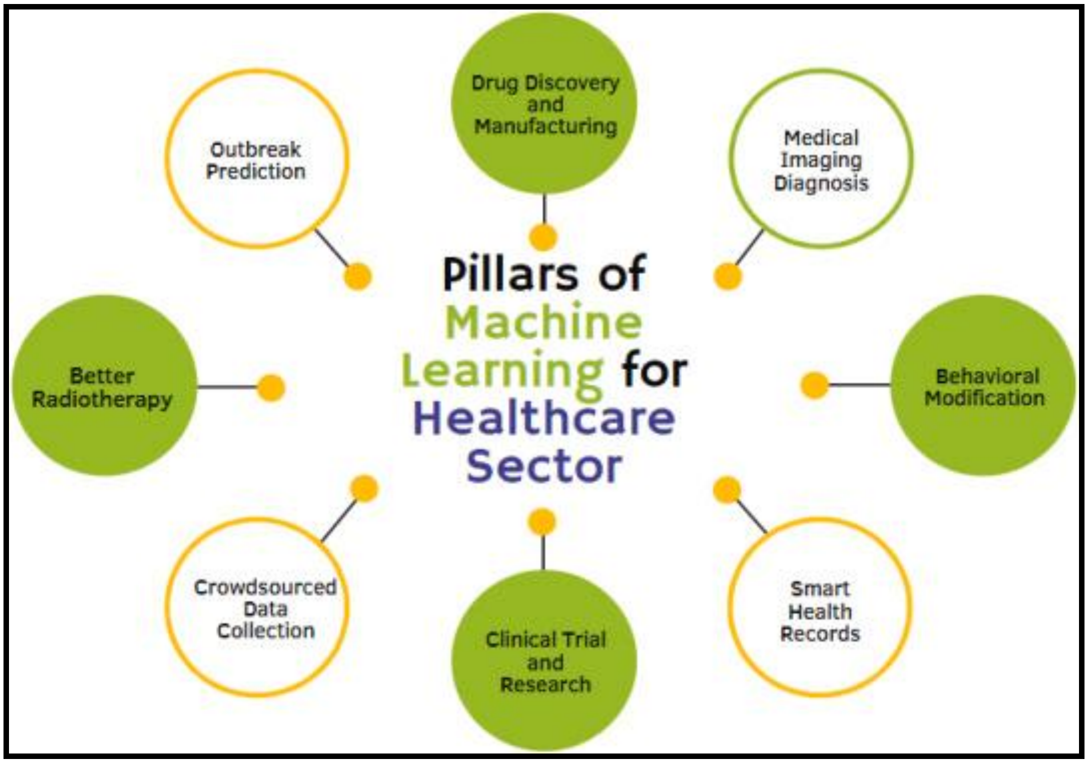

Fig. 3.1: Pillars of Machine Learning for Healthcare Sector

3.2 Model Development

In the process of model development, the required machine-learning algorithms are selected depending on the problem and data. To begin with, the choice of models is dependent on the characteristics of the patient engagement data; features, as well as the target variable. Some of the preferred algorithms for performing this task are characteristic trees, support vector machines, and neural networks. Then each model is fitted in a training data set where the model looks for the pattern or the relation. Hyperparameters are variables that are defined before algorithm execution and these are tuned to help in fine-tuning the performance of the model [25]. To measure the models' stability, a method of cross-validation is often used to check for consistency across different splits of data. The training process also involves the use of regularization techniques in a bid to avoid overfitting. Subsequently, the evaluation of aspects like accuracy, precision, recall, and F1-score is calculated to measure the effectiveness of the models.

Step	Description	Tools/Techniques
Data Collection	Gather supply, demand, and cost data.	Surveys, Databases, Data APIs
Data Preprocessing	Clean and organize data for analysis.	Python (Pandas), R
Model Development	Formulate the optimization model with variables and constraints.	Mathematical Formulation, Linear Programming
Model Solution	Apply optimization algorithms to solve the model.	Simplex Method, Interior Point Method, Solver Tools
Model Evaluation	Assess the performance of the model and solution.	Sensitivity Analysis, Performance Metrics
Result Interpretation	Analyze results and derive actionable insights.	Data Visualization Tools, Statistical Analysis

Table 1: Methodology Overview

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3.3 *Model Evaluation*

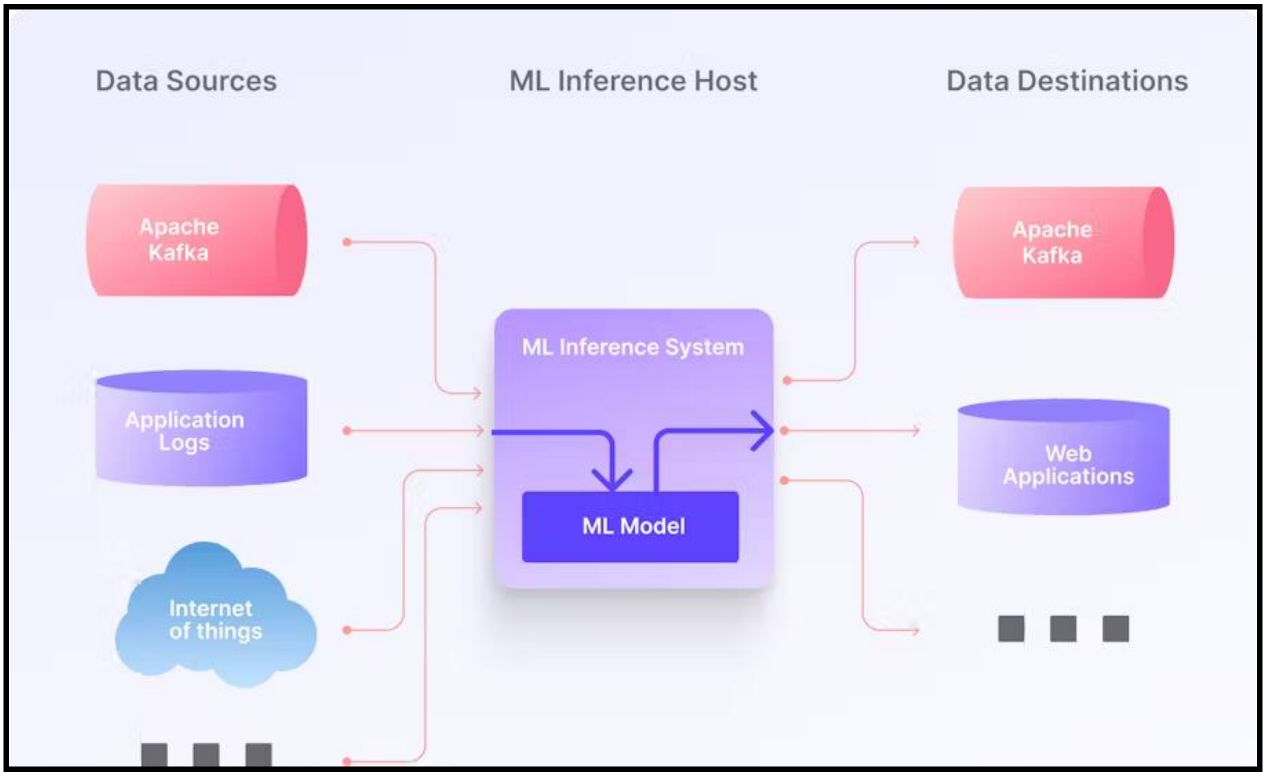

Fig. 3.3: Model Inference in Machine Learning

Evaluation of the model entails analyzing the performance of developed machine learning algorithms in line with stipulated parameters. Some of them are accuracy, precision, recall, and F1 score; these tell the performance of the model. Accuracy defines the percentage of right classification concerning the global size of the test sample [26]. In one round, Precision shows the measure of true positives compared to target positives and Recall reveals true positives as a percentage of actual positives. F1 score is one of the most common metrics that unifies precision positives together. Besides this, confusion matrices can be used also to visualize the performance and detect cases of misclassification. To make sure that the model predicts well on unseen data, techniques like k-fold cross-validation can be used in which the data is split into different parts.

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"Z=4x11+6x12+8x13+5x21+7x22+9x23

Demand at Point 1: x11+x21≥20x_{11} + x_{21} \geq 20x11+x21≥20

Demand at Point 2: x12+x22≥30x_{12} + x_{22} \geq 30 x 12+x 22≥30

Demand at Point 3: x13+x23≥25x_{13} + x_{23} \geq 25x13+x23≥25

Supply from Supplier 1: x11+x12+x13≤40x_{11} + x_{12} + x_{13} \leq 40x11+x12+x13≤40

Supply from Supplier 2: x21+x22+x23≤35x_{21} + x_{22} + x_{23} \leq 35x21+x22+x23≤35

xij≥0 for all i and j"

IV. RESULT AND DISCUSSION

4.1 Result

[6]:

	Patient ID	Age	Gender	Condition	Medication	Treatment Duration (weeks)	Appointment Attendance (%)	Medication Adherence (%)	Engagement Score	Health Outcome	Engagement Level
0	1	45	Male	Diabetes	Metformin	12	85	92	78	Improved A1C	Low
1	2	32	Female	Hypertension	Lisinopril	8	92	88	85	Stable BP	High
2	3	60	Male	Asthma	Inhalers	6	78	95	82	Reduced ER visits	High
3	4	50	Female	Depression	SSRIs	16	90	85	80	Improved Mood	Low
4	5	65	Male	Osteoarthritis	NSAIDs	10	80	90	75	Reduced Pain	Low
5	6	55	Female	Heart Disease	Beta-blockers	14	88	85	79	Stable Heart Rate	Low
6	7	40	Male	Anxiety	Benzodiazepines	9	85	92	81	Reduced Panic Attacks	High
7	8	28	Female	Migraine	Triptans	7	95	80	88	Reduced Headaches	High
8	9	48	Male	Chronic Pain	Opioids	11	75	88	76	Improved Functionality	Low
9	10	38	Female	Allergies	Antihistamines	5	85	95	84	Reduced Symptoms	High
10	11	55	Male	Type 2 Diabetes	Insulin	20	82	85	77	Stable Blood Sugar	Low
11	12	42	Female	Hypothyroidism	Levothyroxine	15	88	90	83	Improved Thyroid Levels	High

Fig 4.1: First few rows of the dataset

The exploration of the dataset is initially done through The dataset comprised of different features that are associated with patient demography, diseases, drug prescriptions, length of treatment, appointment punctuality, compliance to drug prescription, engagement rates, health status, and levels of engagement. This figure displays a glimpse of the first few rows of the

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dataset to help appreciate the structure of the data and the type of information that is being gathered [27].

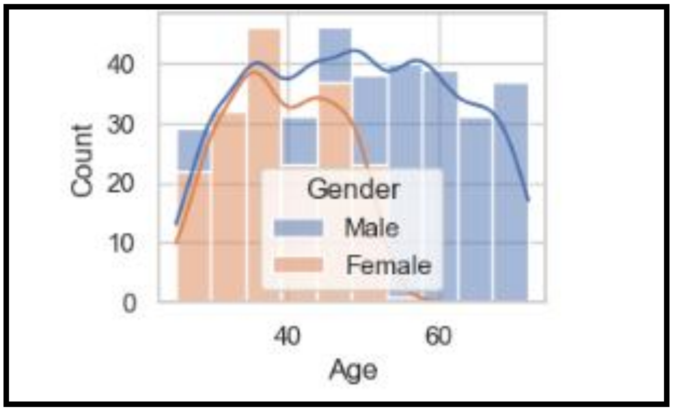

Fig 4.2: Age and Gender Distribution

Age and gender are some of the demographic features that help in analyzing the demographic characteristics of the patients. The figure below shows the number of patients who can be classified into the different engagement levels; Low, Medium, and High. This count plot gives a better picture of where patients are with regards to the scores, where more effort might be needed in trying to keep the patients interested, or whether there is a need to investigate why certain patients are less active.

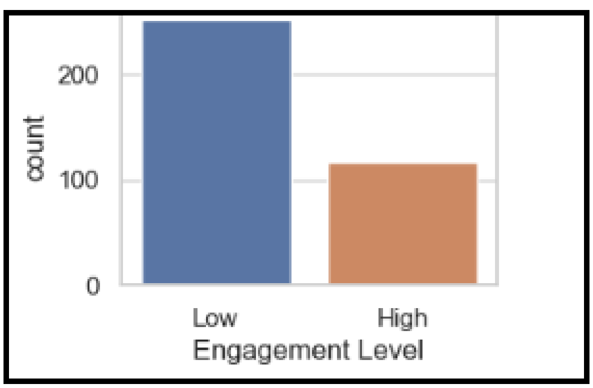

Fig 4.3: Engagement Level Distribution

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It is therefore important to know what proportion of patients is in what level of engagement to be able to have an overall appraisal of the status. The figure below shows the number of patients who can be classified into the different engagement levels; Low, Medium, and High. This count plot gives a better picture of where patients are with regards to the scores, where more effort might be needed in trying to keep the patients interested, or whether there is a need to investigate why certain patients are less active.

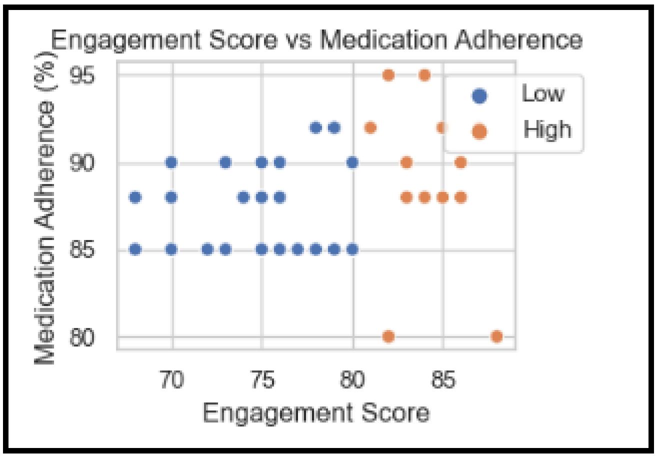

Fig 4.4: Engagement Score vs Medication Adherence

It is also essential to ensure patients take their prescribed medications as prescribed; this is because medication compliance is critical to effective treatment. The graph above shows the correlation between the engagement scores and the medication adherence percentages classified according to engagement classification. It is marked on this type of scatter plot that depicts the levels of engagement with adherence rates [28]. A positive association indicates that better medication adherence is linked to higher engagement scores, which showcases engagement strategies.

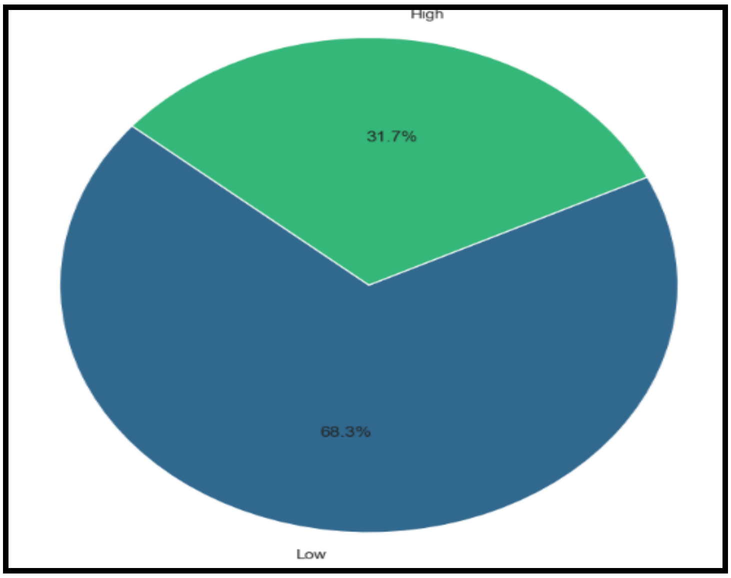

Fig 4.5: Distribution of Engagement Levels

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In this pie chart, the proportions of the consolidated degrees of engagement for patients are depicted as follows. It shows that 68. 3% of the patients are identified as low utilizers while the remaining 31. 7% have high engagement.

```
# Print accuracy scores
print("Logistic Regression Accuracy: {:.2f}%".format(log_reg_accuracy * 100))
print("Random Forest Accuracy: {:.2f}%".format(rf_accuracy * 100))
print("Gradient Boosting Accuracy: {:.2f}%".format(gb_accuracy * 100))

Logistic Regression Accuracy: 98.65%
Random Forest Accuracy: 100.00%
Gradient Boosting Accuracy: 100.00%
```

Figure 4.6: Accuracy Score of each model

This figure shows a summary of the accuracy scores for three different machine learning models of the patient engagement level prediction. The accuracy of the model adopted by this study, namely the Logistic Regression model, is found to be 98. 65%, which is also quite good but slightly less than that of the ensemble methods. This is so because, with the Random Forest, the accuracy score stands at 100 percent, while that of the Gradient Boosting is also at 100 percent.

	precision	recall	f1-score	support
0	0.96	1.00	0.98	22
1	1.00	0.98	0.99	52
accuracy			0.99	74
macro avg	0.98	0.99	0.98	74
weighted avg	0.99	0.99	0.99	74

Figure 4.7: Classification Report for Logistic Regression

This image shows the classification report for the logistic regression model, which indicates how well it predicts patient engagement levels. For the 'Low' engagement class (0), the model achieves an F1-score of 0.98, a recall of 1.00, and a precision of 0.96 with 22 instances of support. 52 occurrences of perfect precision, recall values of 1.00, and an F1-score of 0.98 are recorded for the 'High' engagement class (1) [29]. The overall accuracy is 0.99, indicating strong model performance, with macro and weighted average F1-scores of 0.99 each, which show balanced performance across both classes.

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	precision	recall	f1-score	support
0	1.00	1.00	1.00	22
1	1.00	1.00	1.00	52
accuracy			1.00	74
macro avg	1.00	1.00	1.00	74
weighted avg	1.00	1.00	1.00	74

Figure 4.8: Classification Report for Random Forest

This figure displays the classification report of the Random Forest model. Every metric displays the model's performance. With support for 22 and 52 examples, respectively, the model achieves a precision, recall, and F1-score of 1.00 for both the 'Low' (0) and 'High' (1) engagement classes. The overall accuracy of the model is 1.00. The weighted average and macro F1-score of 1.00 show how exactly and reliably the model determines patient participation levels.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	22
1	1.00	1.00	1.00	52
accuracy			1.00	74
macro avg	1.00	1.00	1.00	74
weighted avg	1.00	1.00	1.00	74

Figure 4.9: Classification Report for Gradient Boosting

This figure presents a classification report of the Gradient Boosting model, where the metrics are identical to those of the Decision Tree model – the model has 100% accuracy in the cases. The gross model with 22 and 52 supporting examples respectively gives the current model a precision, recall, and F1-score of 1. 00 for both the ‘Low’ (0) and ‘High’ (1) engagement classes, The Output of Objective 4 is displayed below; The overall accuracy, therefore, turns out to be 1. 00. The macro F1-score and the crossed weighting with the relative size of the data sets is 1. 00, this means that the engaged patient in the prediction acute model is accurate at a level with no misclassified levels in the patient engagement.

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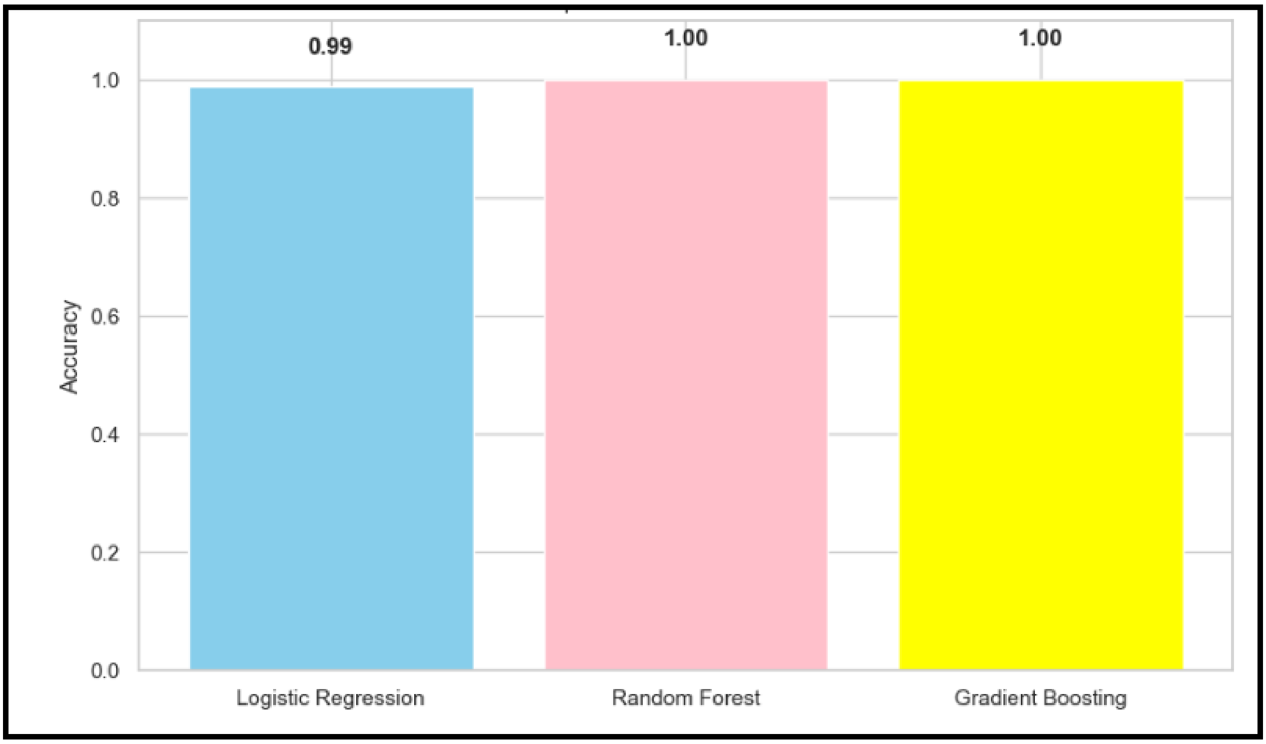

Figure 4.10: Comparison of Model Accuracies

This figure illustrates the differences in accuracy between three machine learning algorithms relevant to patient engagement prediction. In the case of the current model, the Logistic Regression model has an accuracy of 99%, with both the Random Forest and Gradient Boosting models being 100% accurate.

4.2 Discussion

The findings of this study demonstrate that various machine learning models are highly accurate at predicting patients' degree of participation. In this study, there are two machine models are achieve good accuracy that is 100%. The patients' histories, their rates of activity, and the relationship between them and medication compliance are among the details that can be learned from the data. This is supported by the classification reports and accuracy scores, which demonstrate the dependability of the models—particularly the ensemble approaches.

Model	Accuracy	Precision (Low)	Recall (Low)	F1-Score (Low)	Precision (High)	Recall (High)	F1-Score (High)
Logistic Regression	98.65%	0.96	1.00	0.98	1.00	0.98	0.98
Random Forest	100%	1.00	1.00	1.00	1.00	1.00	1.00
Gradient Boosting	100%	1.00	1.00	1.00	1.00	1.00	1.00

Table 2: Accuracy and Classification Report

V. CONCLUSION

This study reveals that; depending on the index being used, some machine learning models are rather accurate in predicting patient engagement levels and the best approaches identified include Random Forest and Gradient Boosting. It can be observed that Logistic Regression also performs satisfactorily achieving an accuracy of 98. 65% accuracy, yet the proposed ensemble methods yield 100% accuracy. These findings suggest that with narrower and precise measures of, and predictions about, engagement, machine learning could significantly enhance the level of patient engagement and deliver more effective and personalized treatment plans.

Therefore, according to the results of this intervention, it can be advised that such machine learning-based approaches should be integrated into the currently existing healthcare systems of various organizations to improve patient engagement [30]. These models should be used to analyze the levels of patient activity on a continual and timely basis in order to detect problems propose solutions and integrate patient care to predetermine plans. Further, other intervention research ought to evaluate how these models fare over time in relation to patient adherence and outcomes, as well as transportability across different disorders and patient populations. The dynamic aspect can be addressed by periodically updating models in an effort to improve adherence as well as the results achieved through feeding real-time data into the models.

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