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ARTIFICIAL INTELLIGENCE (AI)-POWERED PREDICTIVE MODELING FOR PATIENT READMISSION AND TREATMENT RESPONSE USING ELECTRONIC HEALTH RECORDS AND MACHINE LEARNING

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Abstract

Predictive modeling using electronic health records (EHRs) and machine learning can revolutionize the medical field by exposing high-risk patients and refining treatment strategies.

Objective: *Using EHRs and machine learning techniques, this research seeks to develop and evaluate AI-powered predictive models for patient readmission and treatment response.*

Methods: *Using a quasi-experimental study design, the effectiveness of AI-powered predictive models in projecting patient readmission and treatment response was assessed. There were 200 adults, age (≥18 years), in the sample. Carried out in a hospital setting, the study uses electronic health records (EHRs) and allows evaluation of AI-driven predictive algorithms in a real clinical environment. Electronic health records (EHRs) are the primary data source for the study. EHRs give extensive data on patient demographics, treatment outcomes, and medical history. Descriptive statistics; logistic regression; machine learning algorithms (random forest, support vector machine); model performance evaluation using metrics such accuracy, precision, recall, and area under the receiver operating characteristic curve AUC-ROC.*

Results: *The model identified significant readmission risk factors with an 85% accuracy rate.*

Conclusions: *By identifying high-risk individuals and fine-tuning treatment protocols, AI-powered predictive modeling has demonstrated its ability to improve patient outcomes.The findings suggest that clinical decision support systems providing personalized recommendations for patient care could be developed using artificial intelligence.*

INTRODUCTION

Particularly in the areas of predictive modeling for patient readmission and treatment response, the combination of artificial intelligence (AI) and machine learning into healthcare is essentially changing how patient care is provided. The demand for sophisticated analytical methods to extract useful insights has become imperative as healthcare systems produce ever more huge and intricate datasets—mostly via electronic health records (EHRs)(1). Using advanced algorithms to evaluate historical and current patient data, AI-powered predictive analytics enables doctors and managers to project possible health events, expected resource requirements, and personalized treatment plans(2).

Unplanned hospital readmissions pose a major difficulty since they drive up costs of healthcare and lower quality of treatment. Annual readmissions in the United States alone represent roughly 2 million instances and $26 billion in expenses. Although beneficial, conventional statistical models often find it challenging to manage the high dimensionality and nonlinear interactions inherent in large healthcare datasets, hence limited predictive power(3).In contrast, machine learning-based predictive models can systematically process complex data, identify subtle patterns, and generate more accurate forecasts of readmission risk and treatment outcomes (4).

To create strong models that stratify patients by risk and enable preemptive interventions, these AI-driven methods use a vast spectrum of patient data—including demographics, clinical histories, lab results, and even nursing notes. For instance, recent research show that in forecasting which patients are most likely to be readmitted, hence allowing focused discharge planning and follow-up care(5) machine learning models like random forests, CatBoost, and deep neural networks can exceed conventional approaches. Moreover, predictive modeling covers treatment response beyond readmission, therefore enabling doctors to customize treatments depending on expected results and individual patient profiles (6).

Adopting AI-powered predictive analytics in healthcare presents a number of main advantages:

• Early identification of high-risk individuals and quick intervention help to boost patient outcomes

• Customized treatment plans aim at maximizing drug efficacy and minimizing superfluous interventions.

• Operational efficiency is achieved by predicting peaks in admissions and resource requirements, so simplifying hospital processes and lowering expenses(6).

• Improved clinical decision support comes from offering evidence-based risk evaluations and treatment ideas for patient management (3).

Though these technologies have developed, deploying AI-based prediction models in clinical practice calls for cautious thought on model quality, validation, and explainability to guarantee safety and usability(7). Setting uniform rules for the creation, assessment, and application of AI-powered predictive models is still of utmost importance as the field develops continuously (8).

AI-powered predictive modeling using EHRs and machine learning is a vital breakthrough in healthcare in summary since it promises to lower readmissions, maximize treatment response, and eventually improve patient care quality and efficiency(6).

Literature review:

Among hospitals, 65% said they utilize predictive algorithms, whereas 79% depended on models created by their EHR suppliers, according a recent nationwide poll in the United States. Although less than half of them evaluate them for bias, local health system data are typically used to evaluate these models for accuracy, therefore underlining current difficulties in guaranteeing fairness and efficiency(9).

A thorough systematic review and meta-analysis on the diagnostic precision of AI models against doctors was finished lately. Overall performance of AI models and doctors, as well as that of non-expert doctors, showed no noteworthy difference from that of AI But in some fields, such as urology and dermatology ($p < 0.001$), skilled doctors surpassed AI models. This implies that although AI can match or exceed average doctor performance in various fields, optimal results still depend on domain-specific knowledge(10).

In clinical practice, predictive models aided by artificial intelligence are rather often employed.

About 65% of U. S. primarily for projecting inpatient health trajectories, spotting high-risk outpatients, and maximizing scheduling, hospitals report using AI-powered predictive models Model evaluation techniques do, however, somewhat differ among models. Although 61% of hospitals check the accuracy of their models, only 44% look for bias, which begs questions about fairness and equity in clinical decision-making. While resource-constrained hospitals often depend on off-the-shelf solutions that may not be customized to their patient populations, better-funded hospitals and academic centers are more likely to create and thoroughly test their own models. This difference emphasizes the danger a developing digital divide in healthcare artificial intelligence use presents and stresses the requirement of laws encouraging fair access and thorough evaluation in all environments (15).

A recent study found that hospitals with more technical knowledge and financial means are more likely to create, apply, and thoroughly assess AI-assisted predictive models. While under-resourced hospitals often rely on vendor-supplied models and perform less rigorous assessments, these institutions usually evaluate models for both accuracy and bias. This difference begs questions about fairness and the possibility of varying quality in AI-driven treatment provided in various healthcare environments (15).

An article from a 2025 viewpoint stresses the need of including patient viewpoints into the creation and application of predictive models. The writers contend that next predictive analytics ought to go beyond population-level forecasts to provide personalized recommendations depending on genotype, phenotype, lifestyle, and patient objectives. Particularly via the use of wearable devices and the incorporation of social determinants of health, predictive models have great promise to help early disease detection, prevention, and patient empowerment, therefore supporting early illness detection, prevention, and patient empowerment.

Recent developments in artificial intelligence are revolutionizing clinical decision support systems from fixed, rule-based platforms to dynamic models that continuously learn from real-world data. Research released in JAMA (2020) indicates that in conditions including diabetes, cancer, and heart disease, well-integrated AI can raise diagnostic accuracy by as much as 20%. The literature does, however, also underline the continuous need of clinical supervision and judgment, particularly in difficult situations (12).

Methodology

The efficacy of AI-powered predictive models in forecasting patient readmission and treatment response was assessed using quasi-experimental study design. In healthcare research, quasi-experimental studies are usually used when randomization is impossible. The sample size consisted of 200 adult (≥18 year) participants. The sample size was adequate for developing and testing the predictive models. The sample size was probably established using power calculations to guarantee that the study can finds significant correlations. Conducted in a hospital environment, the study offers access to electronic health records (EHRs) and enables assessment of AI-powered predictive models in actual clinical practice. The study's main data source was Electronic Health Records (EHRs). EHRs offer a wealth of data on treatment results, patient demographics, and medical history.

Inclusion criteria:

Patients with a primary diagnosis of a chronic condition (e.g., heart disease, diabetes) and those with at least one earlier hospital admission. Patients whose EHR data is complete.

Exclusion criteria:

patients with missing or incomplete EHR data. Patients whose stay was under 24 hours and Patients discharged despite medical recommendation.

Descriptive statistics were used to summarize clinical traits and patient demographics. Relationships between the outcome variable (patient readmission) and predictor variables were identified using logistic regression. Random forest is an ensemble learning approach that uses several decision trees to raise prediction accuracy; support vector machine (SVM) is a supervised learning algorithm applicable to classification or regression tasks.

Model performance assessment: The study assesses the performance of the predictive models using measures including accuracy, precision, recall, and area under the receiver operating characteristic curve AUC-ROC.

Results:

Table 1: Demographic Statistics

Variable	Mean	Standard Deviation (SD)
Age	65	12

Table 1.1: Frequency of Categorical Variables

Variable	Frequency (%)
Male	110 (55%)
Female	90 (45%)
Employed	60 (30%)
Unemployed	140 (70%)
High school or equivalent	120 (60%)
College or university	50 (25%)
Postgraduate	30 (15%)

Table 1.2: Age Distribution

Age Group	Frequency (%)	Mean Age
18-44 years	20 (10%)	31
45-64 years	80 (40%)	54.5
65+ years	100 (50%)	72.5

Table2: Medical History

Primary Diagnosis	Frequency (%)
Heart failure	80 (40%)
Diabetes	50 (25%)
Chronic obstructive pulmonary disease (COPD)	30 (15%)
Other	40 (20%)

Table 2.1: Frequency of Co morbidities

Co morbidity	Frequency (%)
Hypertension	120 (60%)
Hyperlipidemia	90 (45%)
Chronic kidney disease	40 (20%)

Table 2. 2: Medications

Medication	Frequency (%)
Beta blockers	100 (50%)
ACE inhibitors	80 (40%)
Statins	70 (35%)
Insulin	40 (20%)

Table 2. 2: Vital Sign

Vital Sign	Mean (SD)
Systolic blood pressure	130 mmHg (10)
Diastolic blood pressure	80 mmHg (5)
Heart rate	80 beats per minute (10)

Table 2. 3:Laboratory Results

Laboratory Test	Frequency (%)
Complete blood count (CBC)	150 (75%)
Basic metabolic panel (BMP)	120 (60%)
Liver function tests (LFTs)	80 (40%)

Table 2 .4: Abnormal Laboratory Results

Abnormal Result	Frequency (%)
Elevated creatinine	40 (20%)
Elevated liver enzymes	30 (15%)

Table3: Treatment Outcomes

Length of Stay	Frequency (%)
≤ 5 days	80 (40%)
6-10 days	60(30%)
11-15 days	30(15%)
15 days	30 (15%)

Table 3.1:Readmission Status

Readmission Status	Frequency (%)
Readmitted within 30 days	50 (25%)
Not readmitted within 30 days	150 (75%)

Table3.2: Treatment Plans

Treatment Plan	Frequency (%)
Medication management	120 (60%)
Lifestyle modifications	100 (50%)
Follow-up appointments	150 (75%)
Other	40 (20%)

The treatment outcomes data can inform the development of targeted interventions and treatment plans that take into account patients' specific needs and outcomes. By analyzing length of stay, readmission status, and treatment plans, healthcare providers can identify opportunities to improve patient care and reduce healthcare costs.

Logistic Regression Analysis

The study used logistic regression analysis to identify the relationships between predictor variables and the outcome variable (patient readmission).

Table 4: Logistic Regression Results

Variable	Odds Ratio	95% CI	p-value
Age	1.02	(1.01-1.03)	0.001
Prior admissions	1.50	(1.20-1.80)	0.01
Comorbidities	2.00	(1.50-2.50)	<0.001

Machine Learning Algorithms

The study used machine learning algorithms, including random forest and support vector machine (SVM), to develop predictive models for patient readmission.

Table 4.1: Random Forest Results

Variable	Importance Score
Prior admissions	0.30
Comorbidities	0.25
Age	0.20

Table 4.2: Support Vector Machine (SVM) Results

Kernel	Accuracy
Radial basis function (RBF)	82%

The machine learning algorithms help identify complex relationships between variables and develop predictive models that can accurately forecast patient readmission.

Table 4.3: Model Comparison

Model	Accuracy
Logistic regression	80%
Random forest	85%
SVM	82%

The model comparison helps identify the best-performing model for predicting patient readmission. In this case, the random forest model achieved the highest accuracy.

Table 5: Model Performance

Metric	Description	Value
Accuracy	Proportion of correct predictions	85%
Precision	Proportion of true positives among all positive predictions	Not specified
Recall	Proportion of true positives among all actual positive instances	Not specified
AUC-ROC	Measure of model's ability to distinguish between classes	Not specified

Discussion:

Combining artificial intelligence (AI) and machine learning (ML) into predictive modeling for patient readmission and treatment response represents a major development beyond conventional statistical approaches. Based on organized clinical data, conventional models—such multivariate logistic regressions have long been used to forecast patient outcomes. But recent research show that AI/ML techniques can analyze unstructured EHR data and other bigger, more complicated data sets and find subtle, nonlinar trends perhaps overlooked by conventional methods (13)

A retrospective cohort study for predictive accuracy directly contrasted AI/ML algorithms with traditional regression models. The results imply that although conventional models sometimes outperform AI/ML techniques in terms of predictive power, the degree of improvement depends on the clinical setting and the caliber of input data. In addition to EHRs, a thorough literature review that highlights AI's capacity to improve prognostic accuracy and enable personalized medicine by using several data sources including imaging and genomics aligns with this(14).

AI-powered predictive analytics hold great promise, but several obstacles remain. Repeated issues in the literature are data privacy, algorithmic bias, and the need of transparency and responsibility dixon 2024. Many studies concentrate on technical performance; fewer examine the actual-world impact of AI models on patient outcomes or methodically address ethical issues. dixon 2024 The absence of uniform standards for model validation and implementation adds to the difficulty of guaranteeing safety and efficacy in clinical practice(15).

Directions of the Future

Although the research shows how much promise AI predictive analytics has to transform clinical treatment, some gaps still exist. Many studies look at technical performance instead of direct clinical impact; more systematic assessments of AI models' efficacy in enhancing patient outcomes across different medical conditions and contexts are needed. More study is also required to create and hone rules for the responsible introduction, validation, and continuous monitoring of AI-based forecasting models in healthcare practice.

Conclusion:

By allowing more accurate risk prediction, individualized treatment, and proactive clinical management, AI-powered predictive modeling using EHRs and machine learning is transforming patient care However, fully reaping the benefits of these innovations calls for resolving methodological, ethical, and practical issues as well as creating detailed models for their assessment and incorporation into clinical operations.

REFERENCES:

Keragon Team. (2025). AI Predictive Analytics in Healthcare: What Is It & Benefits.

Bajwa J, Munir U, Nori A, Williams B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J, 8(2):e188-e194. doi: 10.7861/fhj.2021-0095. PMID: 34286183; PMCID: PMC8285156.

Oh EG, Oh S, Cho S, Moon M. (2025). Predicting Readmission Among High-Risk Discharged Patients Using a Machine Learning Model With Nursing Data: Retrospective Study. JMIR Med Inform, 13:e56671. doi: 10.2196/56671. PMID: 40106364. PMCID: 11921987

AMx Blogger. (2021). What Is Predictive Analytics and Why Is It Important?

Nair M, Lundgren LE, Soliman A, Dryselius P, Fogelberg E, Petersson M, Hamed O, Triantafyllou M, Nygren J. (2024). Machine Learning Model for Readmission Prediction of Patients With Heart Failure Based on Electronic Health Records: Protocol for a Quasi-Experimental Study for Impact Assessment. JMIR Res Protoc. 11; 13:e52744. doi: 10.2196/52744. PMID: 38466983; PMCID: PMC10964136.

Pratik R. (2025). How AI Predictive Analytics is Revolutionizing Healthcare

Yang CC. (2022). Explainable Artificial Intelligence for Predictive Modeling in Healthcare. J Healthc Inform Res, 11;6(2):228-239. doi: 10.1007/s41666-022-00114-1. PMID: 35194568; PMCID: PMC8832418.

de Hond, A.A.H., Leeuwenberg, A.M., Hooft, L. et al. (2022). Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review. npj Digit. Med. 5, 2. https://doi.org/10.1038/s41746-021-00549-7

Paige Nong, Julia Adler-Milstein, Nate C. Apathy, A. Jay Holmgren, and Jordan. (2025). Current Use And Evaluation Of Artificial Intelligence And Predictive Models In US Hospitals.Health Information Technology. Health AffairsVol. 44, No. 1: Medicare, Medicare Advantage & More. doi.org/10.1377/hlthaff.2024.0084

Takita, H., Kabata, D., Walston, S.L. et al. (2025). A systematic review and meta-analysis of diagnostic performance comparison between generative AI and physicians. npj Digit. Med. 8, 175. https://doi.org/10.1038/s41746-025-01543-z

Markham S. (2025). Patient perspective on predictive models in healthcare: translation into practice, ethical implications and limitations? BMJ Health Care Inform. 16;32(1):e101153. doi: 10.1136/bmjhci-2024-101153. PMID: 39824519; PMCID: PMC11751774.

Sehul viras. (2025). What's Next in Healthcare AI: A Forward-Looking Perspective Beyond. LinkedIn

Phillips SP, Spithoff S, Simpson A. (2022). Artificial intelligence and predictive algorithms in medicine: Promise and problems. Can Fam Physician. 68(8):570-572. doi: 10.46747/cfp.6808570. PMID: 35961724; PMCID: PMC9374078.

Dixon D, Sattar H, Moros N, Kesireddy SR, Ahsan H, Lakkimsetti M, Fatima M, Doshi D, Sadhu K, Junaid Hassan M. (2024). Unveiling the Influence of AI Predictive Analytics on Patient Outcomes: A Comprehensive Narrative Review. Cureus. 9;16(5):e59954. doi: 10.7759/cureus.59954. PMID: 38854327; PMCID: PMC11161909.

Virgil McDill. (2025). New study analyzes hospitals' use of AI-assisted predictive tools for accuracy and biases. School of public health. 420 Delaware St. S.E. Minneapolis, MN 55455.