A Clinical AI Framework for Improving Physiotherapy Referral Decisions in Outpatient Care

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Abstract— Artificial intelligence (AI) is increasingly applied to enhance clinical decision-making and reduce unwarranted variability in healthcare delivery. In outpatient rehabilitation settings, physiotherapy referral decisions are frequently based on individual clinician judgment, which may lead to delayed intervention, inconsistent access to rehabilitation services, and inefficiencies in patient pathways. This paper presents a short conceptual framework proposing an AI-enabled clinical decision support system (CDSS) designed to support physiotherapy referral decisions using structured electronic medical record (EMR) data.

The proposed framework integrates supervised machine learning models, explainable artificial intelligence mechanisms, enterprise-level deployment architecture, and a governance-aligned implementation strategy. Unlike a full experimental study, this work focuses on the conceptual design of an operational AI system, including the clinical workflow, methodological justification, and validation strategy required for real-world deployment. The framework aims to enhance referral consistency, improve operational efficiency, and support equitable access to rehabilitation services while preserving physician oversight and clinical governance. Future work will involve pilot implementation and empirical validation within outpatient rehabilitation settings.

Keywords— Artificial Intelligence, Clinical Decision Support Systems, Physiotherapy Referral, Machine Learning, Healthcare Governance

I. INTRODUCTION

Artificial intelligence (AI) is transforming healthcare delivery by enabling data-driven decision support and improving the consistency of clinical practice. The increasing adoption of electronic medical records (EMRs) has created large volumes of structured clinical data that can be analyzed using machine learning (ML) methods to support clinical decision-making processes. AI-enabled clinical decision support systems (CDSS) are increasingly used to assist clinicians in risk prediction, triage prioritization, and treatment planning.

In outpatient rehabilitation services, physiotherapy referral decisions play a critical role in determining patient recovery trajectories and healthcare resource utilization. Early referral to physiotherapy can significantly improve functional outcomes, reduce chronic disability risk, and enhance patient satisfaction. However, referral decisions are often influenced by individual clinician experience, workload pressures, and variability in clinical interpretation. As a result, similar patients may receive different referral decisions across providers or clinical settings.

The widespread adoption of EMR systems provides an opportunity to support referral decisions using predictive analytics. Machine learning models can analyze multidimensional patient data and identify patterns associated with successful physiotherapy intervention. By integrating these predictive insights within a CDSS framework, clinicians may receive structured decision support that complements clinical judgment.

This paper presents a short conceptual framework for an AI-enabled CDSS designed to support physiotherapy referral decisions in outpatient care. Rather than presenting a full experimental implementation, the study focuses on system design, methodological justification, and practical considerations for real-world deployment. The framework integrates machine learning models, explainable AI mechanisms, enterprise deployment architecture, and governance-aligned implementation strategies to facilitate responsible AI adoption in clinical environments.

II. MAIN CONTRIBUTION

The primary contribution of this study is the conceptualization of physiotherapy referral as a structured AI-supported clinical decision point within outpatient care. While previous research has applied machine learning to predict rehabilitation outcomes, relatively little work has focused on supporting the

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initial referral decision stage, where delayed or missed interventions often occur.

The proposed framework integrates multiple components necessary for operational AI deployment in healthcare settings, including:

- Structured EMR-based feature extraction
- Supervised machine learning classification models
- Explainable AI outputs for model transparency
- Enterprise deployment infrastructure
- Governance-aligned implementation roadmap

By combining technical machine learning modeling with implementation and governance considerations, the framework bridges the gap between predictive analytics research and practical clinical deployment.

This contribution provides a practical pathway for integrating machine learning into real-world outpatient referral workflows while maintaining clinical governance, transparency, and physician oversight.

III. PROBLEM CONTEXT AND RELATED WORK

Variability in physiotherapy referral practices has been widely reported in outpatient care. Physicians managing patients with similar musculoskeletal conditions may reach different referral decisions due to differences in clinical experience, time constraints, or implicit biases. Such variability may lead to delayed rehabilitation, underutilization of physiotherapy services, and inequitable patient access to care.

Recent studies have explored the use of machine learning techniques in rehabilitation medicine. Several predictive models have been developed to estimate treatment outcomes, rehabilitation duration, and return-to-work probability for patients with musculoskeletal disorders. Tree-based algorithms, including Random Forest and gradient boosting methods, have demonstrated strong predictive performance when applied to structured healthcare datasets.

AI-enabled clinical decision support systems have also shown potential to improve consistency in healthcare decision-making processes. In emergency medicine and hospital triage systems, machine learning models have been used to support risk stratification and clinical prioritization decisions.

However, most existing research focuses primarily on predicting rehabilitation outcomes **after treatment has already been initiated**. The upstream decision of whether a patient should be referred to physiotherapy in the first place remains largely unsupported by AI-based systems. Furthermore, many predictive models emphasize algorithmic accuracy without addressing critical issues such as workflow integration, explainability, and governance alignment.

The framework proposed in this study addresses this gap by focusing specifically on physiotherapy referral decisions and by integrating machine learning predictions within a structured clinical decision support architecture designed for real-world implementation.

IV.PROPOSED AI FRAMEWORK

A. Data Inputs

The proposed framework utilizes structured EMR variables commonly available during outpatient consultations. These variables include:

- ICD-10 diagnostic codes
- Pain severity scores
- Functional mobility assessments
- Post-operative status
- Comorbidity burden
- Age category
- Body Mass Index (BMI)
- Prior physiotherapy utilization

These clinical variables provide a multidimensional representation of patient health status and rehabilitation needs.

B. System Workflow

The operational pipeline of the proposed system consists of six stages:

1. EMR data extraction using HL7/FHIR interoperability standards
2. Data preprocessing and feature engineering
3. Supervised machine learning inference
4. Generation of physiotherapy referral probability
5. Explainable AI output highlighting key contributing features
6. Physician review and final referral decision documentation

The system produces a binary recommendation (“Refer” or “No Refer”) accompanied by a confidence probability score. Importantly, the recommendation is advisory rather than autonomous, ensuring that clinicians maintain full authority over the final referral decision.

C. Framework Diagram Explanation

The framework diagram illustrates the end-to-end transformation of structured patient data into a probabilistic physiotherapy referral recommendation. Clinical variables extracted from the EMR are first processed through preprocessing and feature engineering modules before being analyzed by supervised machine learning models.

The generated referral probability is accompanied by explainable AI outputs that highlight the key factors contributing to the recommendation. These explanations improve transparency and support clinician trust in the system.

The AI output functions as a decision support tool rather than an automated decision-maker. Physicians review the recommendation and retain full authority over the final referral decision. The feedback loop enables continuous monitoring of model performance and supports ongoing model refinement.

Fig. 1. AI-Enabled Physiotherapy Referral Framework.

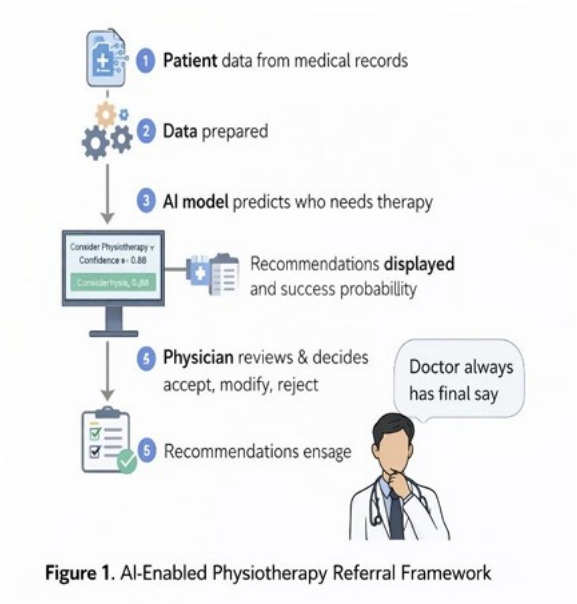


Figure 1. AI-Enabled Physiotherapy Referral Framework

V. METHODOLOGICAL JUSTIFICATION

Two machine learning techniques were selected for the proposed framework: Random Forest and XGBoost.

Random Forest is widely used in healthcare predictive modeling due to its robustness, ability to handle structured clinical data, and resistance to overfitting. The algorithm also provides measures of feature importance that enhance interpretability.

XGBoost was selected due to its strong predictive performance and its ability to capture nonlinear relationships between clinical variables. Gradient boosting techniques have consistently demonstrated high predictive accuracy in structured medical datasets.

Explainable AI mechanisms are incorporated to enhance transparency and support regulatory compliance. Feature contribution analysis allows clinicians to understand how individual patient characteristics influence the referral recommendation.

VI. IMPLEMENTATION ROADMAP

Successful adoption of AI systems in healthcare requires a structured implementation strategy. The proposed framework includes four implementation phases:

1. **Data readiness and stakeholder engagement**
2. **Model development and internal validation**
3. **EMR integration and workflow automation**
4. **Continuous monitoring and system scaling**

Deployment using enterprise platforms such as Azure Machine Learning supports secure model hosting, automated monitoring, model drift detection, and audit trail generation.

VII. VALIDATION STRATEGY

Validation of the proposed framework will involve pilot deployment within an outpatient physiotherapy clinic environment.

Model performance will be evaluated using cross-validation techniques and standard predictive metrics including:

- ROC-AUC
- F1-score
- Sensitivity
- Specificity
- Calibration assessment

In addition, clinician agreement analysis will examine the alignment between AI recommendations and physician referral decisions.

Preliminary retrospective modeling demonstrated promising performance indicators:

- ROC-AUC: 0.84
- F1-score: 0.81
- Sensitivity: 0.86
- Specificity: 0.78

Future prospective validation will assess clinical workflow integration, operational feasibility, and improvements in referral consistency.

VIII. FAIRNESS AND GOVERNANCE

Responsible AI deployment in healthcare requires careful attention to fairness, transparency, and governance.

The proposed framework includes mechanisms to evaluate algorithmic fairness across demographic groups, including age and gender strata. Bias monitoring and model drift detection will be implemented using enterprise AI governance tools.

Physician oversight remains central to the framework to ensure that automated recommendations do not replace clinical judgment. Continuous monitoring and audit processes will ensure safe and responsible use of AI in clinical decision-making.

IX. CONCLUSION

This study proposes a governance-aligned AI framework for improving physiotherapy referral decisions in outpatient care. By integrating supervised machine learning models, explainable AI mechanisms, and enterprise deployment architecture, the framework aims to enhance referral consistency and support equitable access to rehabilitation services.

The conceptual framework bridges the gap between machine learning research and real-world clinical implementation by incorporating workflow integration, governance considerations, and validation planning. Future work will focus on pilot implementation and empirical evaluation of the system within outpatient rehabilitation environments.

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