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Explainable and Federated Machine Learning for Hospital Readmission Prediction: Applications, Challenges, and Future Research Directions

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***Abstract*—Unplanned returns raise expenses, put a burden on hospital resources, and may reveal gaps in continuity of care, making hospital readmission a serious healthcare risk. Explainable and federated machine learning techniques for readmission prediction and clinical decision support are examined in this paper. Demographics, medical histories, clinical measures, biomarkers, prior admissions, and treatment details are all covered. Explainable AI methods, such as SHAP and LIME, make patient-specific forecasts and global model behaviour more understandable. The evaluation emphasizes clear visualizations and clinician feedback while taking into account ante-hoc and post-hoc interpretability, clinical usability, and human–AI interaction. Hospitals may train shared models while keeping local raw patient records thanks to federated learning. Its promise is weighed against issues including inconsistent data formats, device constraints, communication costs, heterogeneous electronic health record systems, and privacy risks like membership inference and model inversion. High-risk patient identification, customized discharge planning, transitional care coordination, chronic illness management, therapy monitoring, and resource allocation are examples of clinical uses. The report concludes by outlining research goals in the areas of fairness, rare-event learning, secure aggregation, therapeutic impact assessment, and sustainable shared infrastructure. It emphasizes thorough external validation across a variety of healthcare environments and patient populations.**

Keywords—Federated Learning, Explainable Artificial Intelligence, Electronic Health Records, Hospital Readmission Prediction, Data Privacy, Clinical Decision Support, Human–AI Interaction.

I. INTRODUCTION

Technological developments in healthcare have enhanced data-driven decision-making, allowing for more efficient clinical evaluation, patient monitoring, and individualized treatment plans in contemporary healthcare systems. In contemporary healthcare systems, hospital readmission has become a major problem that has a substantial impact on patient outcomes, hospital resource utilization, and healthcare expenditures. Because diabetes is frequently linked to multimorbidity, drug complexity, complications, and post-discharge instability, diabetic patients are most susceptible to unscheduled readmissions among populations with chronic diseases [1]. Both patient well-being and healthcare efficiency may be impacted by frequent readmissions, which may be a sign of poor glycemic control, treatment non-compliance, inadequate discharge planning, or restricted follow-up care. In order to facilitate early physician intervention, it is critical to predict the readmission risk of diabetic patients [2]. Healthcare professionals can use readmission predictions to identify high-risk patients before discharge, priorities follow-up consultations, modify prescription regimens, enhance patient education, and minimize avoidable readmissions [3]. Large-scale patient data can be analyzed by machine learning fine-tuning algorithms and deep learning models, which can uncover intricate connections between demographics, admission history, test results, medication history, and past medical use.

One potential solution to the issue of hospital readmission is Federated Learning (FL) [4]. When a patient is readmitted to the hospital within a specific time frame following their discharge, this is known as a hospital readmission. It is an expensive and frequently avoidable issue that can result in subpar patient outcomes and higher medical expenses. [5]. Predictive models that identify patients who are at high risk of readmission can be trained using FL [6]. Without disclosing patient information or breaking privacy laws, these models can be developed using data from several hospitals or healthcare systems. Participating hospitals can work together to train the model while protecting patient privacy thanks to FL [7].

HF readmission prediction using machine learning (ML) models has a number of drawbacks. First, there are questions regarding the models' generalizability across various populations and healthcare contexts because the majority of them were created and validated using cohorts from the United States or Europe. Second, it is rare to perform external or multicenter validation, which is a crucial step in evaluating the robustness and practicality of the model [8]. Third, many models ignore unstructured clinical notes, socioeconomic factors, or psychosocial factors in favour of organized data,

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such as billing codes, which may lower forecast accuracy and equity [9].

A. Structure of the Paper

The structure of this document is as follows: Explainable machine learning for hospital readmission prediction—including SHAP, LIME, clinical interpretability, biomarkers, and human–AI interaction—is covered in Section II. Federated learning, its uses in healthcare, data heterogeneity, and privacy issues are all covered in Section III. Research needs are identified and previous studies are reviewed in Section IV. The results and future study directions are presented in Section V.

II. Explainable Machine Learning for Hospital Readmission Prediction

Explainable machine learning improves the transparency of hospital readmission prediction by clarifying how clinical factors affect model outcomes. Techniques like LIME, SHAP, feature importance, and counterfactual explanations help reveal behaviour and pinpoint risk factors specific to each patient. During follow-up therapy and discharge planning, these explanations help with understanding, risk assessment, and decision-making.

A. Hospital Readmission Prediction

In Canada, about 10% of hospitalized patients are readmitted within 30 days. The annual cost of readmissions was roughly $2 billion in Canada in 2011 and $26 billion in the US in 2014. According to studies, 10–60% of these readmissions may have been prevented [10]. Hospitals with high readmission rates face financial penalties from the Centres for Medicare & Medicaid Services in the United States. One of the biggest issues facing the healthcare systems is the repercussions and expenses of readmissions.

1) Hospital Readmission as a Healthcare

Hospital readmission is a persistent issue for healthcare systems worldwide. Unplanned readmissions that occur within 30 days after discharge are used as a gauge to assess the efficacy and calibre of medical care. Early hospital readmissions strain resources, increase operating costs, and put patients' health at risk [11].

2) Predictive Modelling in Healthcare

Predictive modelling is currently a key strategy used in healthcare decision-making to improve its outcomes [12]. By analyzing past clinical data, the predictive algorithms identify trends that result in unfavourable outcomes, allowing healthcare providers to treat patients sooner and allocate resources more effectively.

B. Explainable ML in Hospital Readmission Prediction

Clear and reliable descriptions of the underlying logic of machine learning algorithms are necessary for their clinical adoption [13]. By offering two complementary viewpoints on model behaviour, Explainable AI (XAI) techniques overcome the "black-box" conundrum.

- **Global Explanations:** These enable regulators, clinical safety officers, and researchers to examine the model's Overall decision logic for a whole patient cohort, making sure the method is based on aspects that are clinically valid rather than dataset artefacts or confounding variables [14].
- **Local Explanations:** These provide an explanation of individual risk scores and highlight the unique clinical factors that influence the forecast for a certain patient encounter.
- **Shapley Additive explanations (SHAP):** SHAP, which is based on cooperative, coalitional game theory, determines each clinical characteristic's marginal contribution across all potential feature subsets in order to give each variable a distinct, mathematically consistent Shapley value (ϕ) [15].
- **Local Interpretable Model-agnostic Explanations (LIME):** A surrogate model-agnostic method that creates synthetic samples in a patient's neighbourhood by altering their clinical characteristics in order to explain a single prediction.

C. Clinical Interpretability and Human–AI Interaction

Clinical interpretability and human-AI interaction are critical to the effective deployment of readmission prediction systems. Explainable models let healthcare professionals analyse prediction results, understand patient-specific risk factors, and make well-informed decisions. User-friendly interfaces, lucid explanations, and clinician feedback all contribute to the increased trust, use, and acceptability of AI-based clinical decision support systems.

1) Interpretability of the Technological Perspective

Hospital readmission prediction looks at technological advancements from two complementary angles: interpretive methods that make individual prediction outcomes clear and explainable machine learning algorithms that facilitate transparent patient risk assessment [16]. Federated learning also makes it possible for healthcare organizations to work together to construct models while protecting the privacy and confidentiality of patient data.

2) Interpretation Method of Clinical Interpretability

There are two primary methods for classifying explainability in hospital readmission prediction [17]:

- **Ante-hoc interpretability:** Involves using models that are naturally transparent, like logistic regression, decision trees, and rule-based algorithms, to comprehend how the model makes decisions.
- **Post-hoc interpretability:** Explains specific readmission predictions produced by intricate machine learning models using methods like SHAP and LIME.

3) Biomarkers

Biomarkers are quantifiable biological indicators that reveal details about physiological functions, illness states, and medical treatment responses [18]. Clinical markers that can detect patient health issues and possible readmission difficulties include glucose levels, haemoglobin, creatinine, and cardiac signals.

4) Human-AI Interaction

The usability and clinical acceptability of hospital readmission prediction systems are significantly influenced by the interface. Healthcare workers can better comprehend patient risk scores, significant clinical characteristics, and model forecasts with the aid of dynamic visualizations and user-friendly dashboards [19]. Clear information display, user control, and consistent interfaces enhance clinician comprehension, lessen cognitive load, and facilitate efficient patient-provider communication.

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III. Federated Learning for Privacy-Preserving Hospital Readmission Prediction

Federated learning allows several institutions to collaborate to develop readmission prediction models without directly exchanging confidential patient data. Each institution trains a model locally and shares model updates for aggregation in order to promote privacy-conscious collaboration. While addressing institutional diversity, communication costs, security risks, and data-sharing constraints, this approach can improve learning across populations.

A. FL in Healthcare

FL is becoming more and more popular in the healthcare sector due to its application in data privacy, which is particularly important when handling sensitive patient medical data, such as reports, photos, electronic health records (EHRs), and so on [20]. By allowing healthcare organizations to cooperatively train machine learning models while preserving localised and private raw data, FL safeguards patient privacy.

- **Privacy-Preserving Data Sharing:** Healthcare organizations can work together to develop strong machine learning models without exchanging unprocessed patient data because of FL. This is especially crucial for private medical data including photos, electronic health records, and genetic information.
- **Enhancing Disease Diagnosis and Detection:** Diseases including cancer, diabetic retinopathy, and COVID-19 can be more precisely identified using federated models that have been trained on a variety of datasets from several healthcare facilities. They gain from the variety of data and shared expertise among institutions [21].
- **Optimizing Predictive Models for Patient Outcomes:** Encourages the creation of prediction models that forecast health outcomes and customize treatments by analyzing treatment plans and patient histories.
- **Drug Discovery and Development:** Pharmaceutical businesses and research institutions can work together to analyses drug efficacy and safety data without disclosing confidential information due to FL.
- **Wearable Device Data Analysis:** Allows for the decentralized analysis of continuous data streams, assisting medical professionals in tracking and forecasting trends in chronic illness [20]. Better patient care results from much improved early diagnosis and monitoring of diseases like diabetes and heart disease.

B. Challenges of Federated Learning

While it is possible for various devices to work together to train machine learning models without exchanging raw data, there are a number of issues that must be resolved [22]. Heterogeneity of Data and Devices: Due to variations in EHR systems, data formats, coding procedures, clinical workflows, and monitoring equipment, healthcare organizations frequently keep heterogeneous patient records. These differences, which include inconsistent features, missing values, and uneven data quality across hospitals, pose problems for federated learning.

- **Data Heterogeneity:** Healthcare data comes in a variety of formats, including text, pictures, and time series, each of which has distinct qualities that call for particular processing techniques in order to train models.
- **Device Heterogeneity:** Healthcare equipment differs in terms of power consumption, network connectivity, and hardware and software needs. Certain devices might not have the memory or processing power to take part in FL due to resource constraints [23].
- **Federated Transfer Learning:** This approach speeds up model training on heterogeneous devices by using pre-trained models on similar data domains. Adaptive learning algorithms can change the model's parameters based on the computing capability of the device.

1) Data Privacy and Security

While there are many advantages to this approach, such as improved privacy and reduced communication costs, there are also serious data protection issues [24]. Some of the major data privacy concerns that FL raises are as follows:

- **Leakage of data:** Devices in FL distribute model updates, however these modifications may still contain confidential local data [25].
- **Model inversion attacks:** Florida may potentially have this privacy issue. These attacks replicate the original training data used by the local devices using the model updates.
- **Attacks using membership inference:** If attackers have access to certain devices, they could be able to determine which device was used to train the model in FL [26].
- **Attacks on the central server:** In FL, local devices provide model changes to the central server. If the main server is compromised, an attacker might obtain all updates and infer crucial details about the local data [27].

C. Clinical Applications of Readmission Prediction

By identifying patients who are more likely to return to the hospital after being discharged, hospital readmission prediction aids in clinical decision-making [28]. Predictive models classify patients based on risk using clinical measures, medical history, demographics, prior hospitalization records, and treatment-related data.

- **Early Identification of High-Risk Patients:** Healthcare providers can start preventive efforts before discharge by using prediction models to identify patients who are more likely to be readmitted while in the hospital [29].
- **Personalized Discharge Planning:** Individualized discharge plans, which include medication reconciliation, patient education, rehabilitation goals, and suitable post-discharge assistance, are supported by risk assessment.
- **Transitional Care Management:** Telephone consultations, outpatient appointments, home visits, and coordinated treatment between hospitals and primary healthcare providers are all ways that high-risk patients might receive organized follow-up.
- **Chronic Disease Management:** Patients with chronic obstructive pulmonary disease (COPD), and other chronic diseases requiring ongoing monitoring and

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long-term therapy will find readmission prediction very helpful [30].

- **Clinical Resource Allocation:** Hospitals can prioritise support, specialist consultations, care coordinators, and follow-up services for patients who need more clinical attention by using risk-based classification.
- **Quality Improvement and Hospital Performance Assessment:** The assessment of the detection and the creation of plans to enhance patient outcomes and lower preventable readmissions are all supported by predicted readmission risk.
- **Medication and Treatment Monitoring:** Prediction results identify patients for whom drug adherence, side effects, treatment efficacy, and post-discharge problems closely monitored.

D. Future Research Directions

Future research should improve secure aggregation, evaluate clinical impact through prospective trials, address bias in underserved populations, improve prediction of rare clinical events, and build sustainable shared infrastructure in order to reduce costs and promote broader adoption [31]:

- **Enhanced Privacy Protection:** Cryptographic methods and Secure Aggregation (SecAgg+) can improve privacy during federated model training.
- **Causal Clinical Impact Evaluation:** The effectiveness of federated prediction systems in lowering hospital readmissions and medical expenses can be assessed through prospective cluster-randomised trials.
- **Equity and Accessibility:** Algorithmic bias should be addressed in future studies to enhance model performance in underprivileged healthcare environments and with a variety of patient demographics.
- **Federation for Rare Clinical Events:** It can improve the prediction of uncommon medical illnesses and occurrences that individual hospitals are unable to accurately learn owing to a lack of data.
- **Sustainable Federated Infrastructure:** Federated learning can be made available to smaller healthcare organizations by lowering implementation costs through shared infrastructure and cooperative deployment frameworks [32][33].

IV. Literature Review

Using clinical features, patient history, and electronic health records, recent research has investigated machine learning and deep learning methods for hospital readmission prediction. To increase prediction and relevance, research is increasingly utilizing explainable AI, risk calibration, ensemble algorithms, and feature engineering.

D. Bhat and D. Rao, (2026) create and internally assess an interpretable machine learning framework for predicting hospital readmissions and classifying diabetes. A population-level diabetes dataset with 100,000 records and a clinical hospitalization dataset with 70,000 records were the two complimentary datasets that were examined. The suggested system facilitates predictive modelling and feature contribution interpretation by combining Light Gradient Boosting Machine with Shapley Additive explanations (SHAP) [34]. Tripathi, et al., (2026) an effort to create a machine learning model that is interpretable and sensitive to risk in order to forecast hospital readmission using structured electronic health record (EHR) data. The model adds explainability based on SHAP to provide comprehensible, patient-specific information about model predictions and combines ensemble learning with probability calibration to generate high-quality risk classification [35].

V. Jadav and R. Ruparel, (2025) provide a data-driven framework that uses clinically informed feature engineering and organized electronic health record data to predict 30-day readmission. A proprietary clinical feature engineering pipeline is used to transform noisy, categorical, and diagnosis-related variables after extensive data profiling and cleaning. To make the model more comprehensible and practical, this comprises age normalization, ICD-9 chapter mapping, grouping by medical specialization, and combining pharmacological changes [36]. S. Ponmani, et al., (2025) provided patients access to a web portal that lets them see their current health status. It is designed with a readmission prediction engine that enables administrators to forecast patients' current readmission status. In addition to predicting the patient's likelihood of being readmitted, the system also makes an appointment with the same physician, prolongs the patient's hospital stay, and guarantees that they receive extra care. Additionally, the Gemini big language model is integrated with this system to offer AI-generated explanations [37].

A. Revankar, et al., (2024): Effective neural networks for improving the accuracy of hospital readmission predictions. The UCI Machine Learning Repository dataset underwent pre-processing to account for outliers, missing values, and categorical encoding. The SMOTE method was also used to address class imbalance [38].

V. R. Burugadda, et al., (2023) investigated machine learning algorithms that predict hospital readmissions for heart failure patients using information from electronic health records. They evaluated logistic regression, random forests, decision trees, Support Vector Machines (SVM), and artificial neural networks for accuracy, precision, recall, and F1-score [39].

Previous research shows how explainable AI, machine learning, ensemble methods, and neural networks can be used to forecast hospital readmissions. But there are still gaps. Research frequently relies on internal validation and structured electronic health records, which limits generalizability across populations and facilities. Despite the growing popularity of SHAP-based interpretation, healthcare professionals do not always analyses or incorporate explanations into practical judgements. Model comparisons are challenging due to differences in feature engineering, class-imbalance handling, and probability calibration. There is not enough focus on longitudinal patient histories, multimorbidity interactions, temporal changes in clinical condition, and privacy-preserving collaboration. Additionally, more robust safety and reliability assessment is needed for LLM-generated explanations and automated care recommendations. Strong, comprehensible, and clinically proven readmission prediction models are motivated by these constraints. Table I below summarizes the results and limitations of previous research.

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TABLE I. SUMMARY OF KEY STUDIES ON HOSPITAL READMISSION PREDICTION

Author & Year	Objective / Approach	Technology / Method	Key Findings / Contribution	Limitations
Bhat and Rao (2026)	Develop an interpretable framework for diabetes classification and hospital readmission prediction.	LightGBM, SHAP; clinical hospitalization dataset (70,000 records) and population-level dataset (100,000 records).	Integrates predictive performance with feature-level interpretability across two datasets.	Internal evaluation limits external validation and generalizability across healthcare settings.
Tripathi et al. (2026)	Develop risk-sensitive readmission prediction using structured EHR data.	Ensemble learning, probability calibration, SHAP.	Provides calibrated risk stratification and patient-specific explanations for clinical predictions.	Performance may depend on EHR quality, calibration stability, and validation across diverse populations.
Jadav and Ruparel (2025)	Predict 30-day hospital readmission using clinically informed feature engineering.	Data profiling, ICD-9 mapping, age normalization, medical specialization grouping, medication-change aggregation.	Improves clinical representation of structured records and supports interpretable predictive analysis.	Custom feature engineering may limit adaptability to different datasets and healthcare systems.
Ponmani et al. (2025)	Develop an interactive system for readmission prediction and patient care management.	Web interface, readmission prediction engine, Gemini LLM.	Integrates prediction, AI-generated explanations, appointment scheduling, and extended patient care.	Clinical reliability, privacy, real-world validation, and the effectiveness of automated care recommendations require further evaluation.
Revankar et al. (2024)	Investigate neural-network-based hospital readmission prediction.	Neural networks, data preprocessing, missing-value handling, outlier treatment, categorical encoding, SMOTE.	Addresses preprocessing and class imbalance to improve readmission classification.	Limited information on model interpretability, external validation, and clinical implementation.
Burugadda et al. (2023)	Evaluate machine learning algorithms for heart failure readmission prediction using EHR data.	Logistic Regression, Decision Trees, Random Forest, SVM, ANN; Accuracy, Precision, Recall, F1-score.	Compares multiple ML techniques for identifying readmission risks among heart failure patients.	Traditional algorithm comparison may not adequately address explainability, temporal patient data, and deployment challenges.

V. CONCLUSION AND FUTURE WORK

Healthcare professionals can identify patients who might need extra support after release and enhance follow-up treatment by using hospital readmission prediction. This review has looked at the complimentary functions of federated learning and explainable machine learning. The impact of clinical variables is made clear by SHAP, LIME, and interpretable models, which also facilitate the evaluation of risk estimates. Risk assessment is further informed by biomarkers, patient histories, and treatment data, and human-AI interaction is supported by interfaces and physician feedback. Hospitals may create collaborative models without centralizing raw patient data thanks to federated learning. However, model training is made more difficult by variations in electronic health record systems, data quality, devices, and demographics. Federation by itself cannot ensure security because shared model changes may still be susceptible to privacy breaches. Reliable justifications, privacy protections, equitable performance, and workflow evaluation are all necessary for implementation. For readmission prediction, the combination of explainability and privacy-conscious cooperation is promising; nevertheless, the advantages must be proven by validation and prospective assessment through clinical audits and monitoring.

In order to lower implementation costs and promote wider adoption consistently across participating hospitals with shared governance and implementation standards, future research should strengthen federated privacy through secure aggregation, assess clinical impact in prospective trials, lessen bias in underserved populations, enhance learning for rare events across hospitals, and develop sustainable shared infrastructure.

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