

Healthcare Data Analytics and Patient Health – A Way Forward to Improve Decision-making and Accountability in Healthcare System

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Abstract

Artificial Intelligence (AI) has been a major factor to transform healthcare delivery and decision-making in healthcare. Computer vision, machine learning, and deep learning are some of the AI techniques widely used in workflows of healthcare institutions to promote risk assessment, diagnosis, and care planning. This study aims to investigate the use of AI in healthcare sector to predict readmission within 30 days among diabetic patients and how it ensures accountability in making decisions. This study is also based on analyzing secondary data collected from previous studies and credible online sources. In addition, secondary data was also collected from a healthcare dataset “Diabetes 130 US hospitals for years 1999-2008” which is publicly available and consists of 101,766 encounters. The 30-day readmission was predicted using Random Forest and Logistic Regression models and performance of AI models was evaluated with precision, accuracy, F1-score, recall, and PR-AUC and ROC-AUC. It is found that AI can deliver vital information related for making clinical decisions to predict readmission of patients at risk. Hence, it is important to assess fairness, auditability, and explainability to determine predictive performance. This study recommends healthcare units to use AI to ensure accountability. Instead of replacing human decision-makers, AI should be used as a helping hand to provide transparent details that will help in decision-making. In addition, AI shows better performance in some tasks, such as, prediction and image-based uses. There is still need to wait until AI matures enough to be reliable in complex environments.

Keywords – *artificial intelligence, healthcare, accountability, decision-making, readmission, diabetes*

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Introduction

Artificial Intelligence (AI) has redefined the landscape of global healthcare system, having transformative potential for patient care, diagnostics, and treatment. With advances in machine learning (ML), AI technologies are growing with significant computation power and digitized data to transform the areas which were once dependent on human experience (Rajpurkar et al, 2022; Kang et al, 2024). From forecasting the trajectories of illnesses to enhancing allocation of resources, AI can address long-term challenges in healthcare sector to improve efficiency, accuracy, and accessibility (Grzybowski et al, 2023; Goktas and Damadoglu, 2025). However, existing studies have overlooked the relationship between regulatory challenges and implementation in real-world, while focusing only on technological advances of AI. In addition, there are different types of AI systems used in healthcare based on risk profiles, interpretability, and accessibility for healthcare (Farah et al, 2023). While decision trees and rule-based AI algorithms are highly transparent, deep learning is usually not easy to interpret in neural networks. However, it can perform better than simpler models in genomics and medical imaging roles. There is a rise of explainable AI (XAI) to balance interpretability and accuracy in clinical settings (Amann et al, 2020; Chaddad et al, 2023). However, it is important to determine whether some types of AI models are inherently

beneficial for healthcare in terms of accountability, feasibility and safety.

AI is posing certain risks which need strong ethical frameworks to expand into healthcare environments. Some of the major concerns are data privacy, patient safety, and uncertain regulations. AI models are usually “black boxes” in healthcare. Care providers may not be capable enough to interpret their decisions or trust their processes (Grzybowski et al, 2024; Goktas, 2024). In an example of medical imaging like radiology and MRI to detect tumors, convolutional neural networks (CNNs) often find it challenging to explain their predictions. So, healthcare professionals may find it challenging to trust and interpret their processes (Tonekaboni et al, 2019). In intensive care units (ICUs), AI-based sepsis prediction has shown utmost accuracy and provided insight on the reasons to assess risks (Cabitza et al, 2020). These are some of the challenges in adopting AI related to data privacy and governance. These problems not only affect trust, but also increases concerns over accountability in case of errors. An interpretable and explainable AI model is needed to increase transparency and trust on its decisions (Zhou et al, 2021).

1.1. Background

Data analysis tools like chatbots, electric health records (EHRs), and dashboards are the indispensable part of healthcare data analytics. They

strengthened scheduling for patients and collection of health data. Instead of just the past codes, they provide patient data to care providers to make predictions on the basis of actionable insights. From the first point of contact to payment and billing, healthcare data is collected. Healthcare data is collected by automated data to schedule, identify, prescribe for, and treat patients (Rahman et al, 2023).

Data visualization tools like dashboards can help healthcare experts to see general health trends, get support with scheduling, staffing, and supply, and efficient practices to understand financial health of a hospital or clinical practice. Decisions can also be automated as per data available to set up a process to send reminders automatically or reallocating resources of a flu outbreak trend appears (Rahman et al, 2023). Healthcare landscape is going through a transformative change with the combination of data-driven approaches and technologies. Data analytics is integrated at the core of this revolution and it is highly promising to redefine the healthcare delivery (Mantaleon, 2023).

The advancement of data analytics tools like wearables, electronic health records (EHRs), and other technologies have ushered in the age of unexpected flow of patient data. Healthcare experts can collect meaningful data with healthcare data analytics from a big dataset. Healthcare data analytics provides unique opportunities to customize medical interventions to meet individual patient needs. In data analytics, patient-centric methods have become the foundation to provide more accurate, personalized, and preventive healthcare model (Rauniyar et al, 2023).

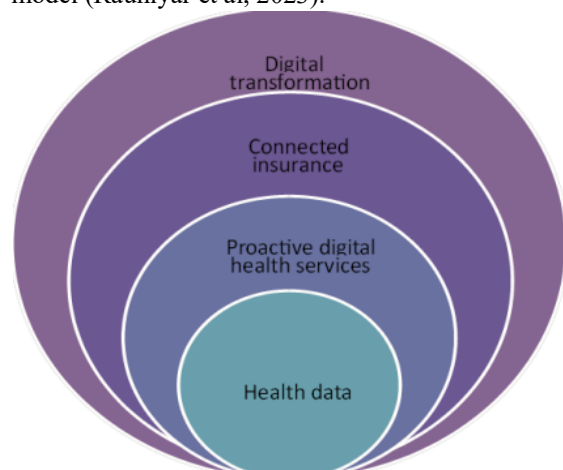


Figure 1 – Emergence of Health Data towards digital transformation

Source – Grundstrom (2020)

Figure 1 illustrates the role of healthcare data to transform healthcare infrastructure. As we move towards the proactive digital health services, there are several ethical challenges which emerge. Careful scrutiny is needed to address issues about data security, patient privacy, and responsible use of data to ensure reliability and integrity of healthcare units.

2. Literature Review

Several approaches and conditions have been created with robust software for collecting and analyzing big data for informed decision-making to address health problems. Galetsi et al (2019) investigated studies related to big data analytics to identify social and organizational challenges in healthcare. They followed PRISMA guidelines for systematic review. They presented challenges, values and future research directions with examples from relevant studies. It is revealed that developing analytical techniques is one of the major values to deliver personalized services to promote human decision-making with automated models to challenge power dynamics in the relationship between doctor and patients. Data security and management are major challenges when it comes to process huge volumes of personal, sensitive health data. Future studies should develop standard systems to extract private datasets from relevant institutions. This study provides better understanding to develop data-based strategy to improve the overall functioning of healthcare units and public health, while addressing challenges in future to avoid issues in societies.

Data science is a complex area which collects insights and knowledge from several unstructured and structured details with data mining, scientific approaches, big data, and machine learning (ML) models. Healthcare sector generates big datasets of vital data on demography, findings of medical exams, insurance, and treatment plans. Internet of Things (IoT) devices collect data and attract data scientists. Data science is helpful to process, analyze, manage, and assimilate a lot of structured, fragmented, and unstructured data. This data needs effective analysis and management to gain factual outcomes. Subrahmanya et al (2022) analyzed the process of data mining, data cleansing, data analysis and data preparation in healthcare units. This study provides insights on the prospects and status of big data analytics to describe the benefits, techniques, and frameworks adopted, challenges faced, and feasible solutions. Big data analytics and data science can deliver practical recommendations to help in decision-making about healthcare system. It provides comprehensive insights to clinicians, patients and consumers to improve quality of healthcare.

There is a rising interest in adopting big data in healthcare sector to manage big data of healthcare organizations like sensor data and patient health data, which are rising in variety and numbers because of the rise of digital devices like wireless sensors and smartphones. Modern healthcare systems need overhaul of traditional paradigms of healthcare hardware/software, which are outdated to deal with diverse health data. Healthcare data analytics is a novel domain for researchers to study big data, find trends and patterns in data, and deliver

a solution to improve services, health access, minimize costs and save valuable lives. Shafqat et al (2020) conducted a study on big data analytics (BDA) in healthcare and several BDA models, tools, and techniques in cloud, IoT, and wireless environments. Finally, a convergence point is formed in all these areas to add to unified healthcare system.

Huge volume of data is being generated in this day and age. Additionally, data is generated in different formats in modern computing solutions, i.e., from unstructured to structured. With exponential growth, strategies, and novel trends, there is a rise of technological advances in big data to improve visibility and data quality in healthcare sectors. Hussain et al (2023) investigated applications and challenges of BDA, while enhancing clinical decision-making. They provided comprehensive insights of approaches and techniques used in BDA in healthcare.

Healthcare decision-makers can improve patient health outcomes and optimize the use of resources with the power of predictive analytics, machine learning, and cloud computing in a highly complex landscape of healthcare. Future of decision-making in healthcare sector is based on constant adoption of ML to stay ahead with changing trends of healthcare sector. Healthcare professionals should work with AI-based decision-support systems (DSS) to make the most of optimal decision-making. Predictive analytics and machine learning have immense potential in areas like managing people's health, personalized medicine, and drug discovery to redefine delivery of treatment. Bayyapu et al (2019) investigated the impact of these technologies in healthcare, existing future research directions, and ethical considerations. They proposed a future with the power of ML, cloud, and analytics where healthcare experts can use data-driven insights to deliver life-saving and tailored outcomes.

2.1. Research Gap

Even though BDA and AI are widely used in healthcare, existing studies have focused majorly on benefits and technical potential, such as, diagnosis, prediction, resource usage, and personalized care. Actual implementation of healthcare data analytics is not discussed widely in recent studies and how it ensures transparency and accountability.

This study fills this research gap by empirically analyzing publicly available dataset of diabetic patients to predict their hospital readmission within 30 days. It contributes to the existing literature by examining AI predictions and consistency across relevant groups of patients.

2.2. Research Objectives

- To discuss the implementation of AI data analytics in decision-making in healthcare
- To explore the role of AI in ensuring accountability in healthcare system by examining predictive performance of AI in

hospital readmissions of diabetic patients with secondary healthcare data

3. Methodology

3.1. Research Approach

This study is based on qualitative research approach to investigate the adoption of healthcare data analytics in decision-making to improve patients' health in healthcare organizations. It helps in exploring the role played by AI to ensure transparency and accountability. This study is focused on exploring and discussing existing applications, knowledge, practices and challenges in healthcare units.

3.2. Data Collection

In this study, secondary data is collected from existing studies published in peer-reviewed journals related to AI in healthcare, big data analytics in healthcare, clinical decision-making with AI, Machine Learning, Predictive Analytics, and accountability in healthcare. The study draws on existing research published from 2020 to 2025 exploring AI, predictive analytics, data analysis, and concerns related to accountability and decision-making. For instance, this study identifies area of data analytics to promote informed decision-making.

In addition, this study investigates publicly available "Diabetes 130 US hospitals for years 1999-2008" dataset having records of diabetic patients about 30-day hospital readmission. The dataset includes 101,766 records of those patients, including demographic profile, clinical variables, information related to diabetes treatment, and healthcare usage.

4. AI in Healthcare Decision-Making

Healthcare sector is being transformed rapidly with AI, especially in terms of decision-making. Care providers have always faced challenge of analyzing big data to make accurate, evidence-based, and timely decisions. However, big data often overwhelms capacity of mankind, i.e., from patient records to lab results and imaging, causing diagnostic errors and missed patterns. AI has been a robust tool to manage those issues. It analyzes long-term, large data to detect patterns which may not be noticed by human decision-makers and provide suggestions to support treatment and diagnosis. Along with improving decision accuracy, this shift also reduces biases, improves patient health, and reduces diagnostic errors (Yu, 2025).

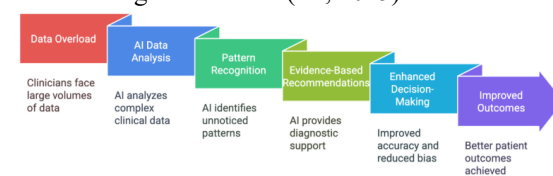


Figure 1 – Steps involved in AI-based decision-making

Source – Yu (2025)

Figure 1 illustrates steps involved in decision-making with AI in healthcare, starting from large

volumes of data to finally making better decisions to improve patient outcomes.

Data overload – It is one of the biggest challenges in decision-making in healthcare institutions. Big data is generated by healthcare systems across the world like lab results, patient health data, imaging data, and genetic data. Healthcare professionals have to synthesize this data instantly, but processing big data in real-time is a major challenge for human brain.

Data Analytics – AI can analyse and process big data with transformative potential. AI models can process millions of GBs of data in real-time by identifying correlations and patterns that human clinicians couldn't detect. AI programs can aggregate data from several sources like –

- Imaging – MRIs, X-ray, ultrasound, and CT scans
- Molecular and genetic information – biomarkers, proteomics, and DNA sequencing
- Remote Sensing and Wearables – glucose levels, heart rate, and activity data

Pattern detection – Machine Learning models are applied by AI after aggregating data to identify relationships and patterns. Large datasets are used to train these models to detect complex patterns which are hard to detect for clinicians. For instance, subtle changes are identified by AI, which suggests early signs of illnesses. Molecular and genetic imaging data can be used by ML models to predict risks. Finally, AI can track unstructured data with “Natural Language processing (NLP)” from clinical notes to identify markers of diagnosis and clusters of symptoms.

Evidence-based Recommendations – AI systems can process data, providing immediate recommendations and knowledge in real-time. For example, abnormal test results can be flagged by AI to suggest follow-up recommendations. AI can help with precision and decision-making in surgery. It can suggest changes to dosage on the basis of how patient responds to treatments.

Enhanced Decision-making – Evidence-based medicine can be provided by AI to make clinical decisions on the basis of comprehensive and most updated evidence available. AI-based tools have been highly accurate to identify diseases like cancer (especially using mammograms to detect breast cancer in early stages), neurological conditions (AI detects Parkinson's and Alzheimer's disease with cognitive results and imaging), and heart disease (to detect early signs of heart disease on the basis of imaging data and EKG patterns).

Improved outcomes – AI provides tailored medicine by providing suggestions on the basis of characteristics of patients, such as, lifestyle, genetics, and medical history. AI can suggest combinations on the basis of genetic profile of patients. Patients' response to some treatments can also be predicted by ML models. AI can recommend

interventions on the basis of real-time data. There are several common biases that can be reduced by AI, such as –

- Confirmation bias – AI delivers alternative solutions instead of strengthening some beliefs.
- Anchoring bias – AI can consider all the data available instead of depending on initial results.
- Availability bias – AI can rely on comprehensive datasets instead of depending on memorable or recent cases.

4.1.Key Pillars of AI-based Healthcare decision-making

For healthcare institutions, there are five key pillars of AI – AI-powered diagnostics, early disease detection, precision medicine, predictive analytics, and smart automation. Each pillar faces certain issues while creating measurable outcomes for healthcare.

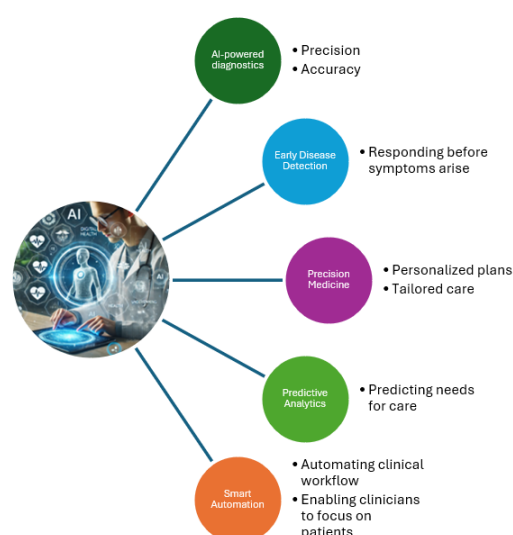


Figure 2 – Use Cases of AI in Healthcare Decision-making

Source – Bhardwaj (2026)

In healthcare decision-making, one of the major areas of AI is based in medical imaging diagnosis and analytics. AI models can track images with accuracy and speed that cannot be achieved by human clinicians. There are millions of medical images like MRIs, CT scans, X-rays, and pathology slides being used to train AI models to detect anomalies that can be the sign of diseases.

4.2.Predictive Analytics

Predicting needs before they come up is a proactive approach adopted by AI-based predictive analytics. It is another breakthrough in healthcare which analyses past data to predict high risks of patients to suggest measures. Hospital readmissions could be reduced by around 25% with this approach, according to McKinsey & Co. (Bestsennyy et al, 2023).

It is one of the essential areas where AI is highly promising. A perfect example of predictive analytics is a health tracking app, Health-e-People, which uses AI for making decisions, analysing personal health

data to forecast health risks and suggest measures. By advising on early health interventions and high-risk groups, this app reduces healthcare expenses by predicting medical conditions to improve patient outcomes (Bhardwaj, 2026) (Figure 3).

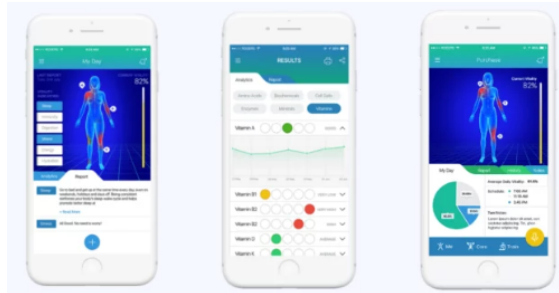


Figure 3 – A screenshot of Health-e-People app used with predictive analytics

Source – Bhardwaj (2026)

Developing apps for medical health diagnosis is a natural point to make AI for decision-making where inputs feed recommendation engines and models to route patients before involving healthcare providers.

4.3.Applications of AI in Healthcare Decision-making

Medical Imaging

Medical imaging is the most recognized area of AI in healthcare with availability of big datasets and visually structured diagnosis. Deep learning have been excellent in some imaging roles and have exceeded or matched radiologists in some areas. A deep learning model has improved performance to reduce false-negative and false-positive rates when screening breast cancer (Uwimana et al, 2025). Autonomous retinopathy has been highly sensitive for diabetic screening and have enabled testing in primary care settings without specialists (Uwimana et al, 2025). Similar benefits have been reported in low-dose screening and chest radiography based on CT scan where AI may help in risk management and early detection (Tabassum et al, 2025).

Most of the imaging studies have been limited irrespective of promising findings. Many studies depend on single-centre groups, reflective research design, and inadequate validation. Hence, performance varies across scanners, populations, and imaging in the dataset (Tabassum et al, 2025). AI has been focused widely on imaging but there is limited benefit of reliable data.

Risk Forecasting for Early Warning

AI models have been developed for predicting risk for acute kidney disease, sepsis, hospital readmission, cardiac arrest, and general issues. Structured patient data is used by these systems to detect subtle patterns in vital signs, lab values, and clinical areas which may lead to extreme outcomes. Both the challenges and promises of this area are observed in sepsis prediction. Even though commercial models have been used widely, performance was worse in external validation of most popular systems, which raises concerns over generalizability, transparency, and reproducibility

(Crider et al, 2022). Some recent models have shown excellent performance for acute kidney injury in more strict standards (Crider et al, 2022). Overall, early warning signs are clinically appealing but their success relies on model performance. Actionability, alert timing, avoiding alert fatigue, and integrating workflow are important to find out whether they cause noise or improve care.

Robotics for Surgical Decisions

AI is widely explored around perioperative areas in surgery, such as, assessing risks before operation, complication risks after operation, intraoperative support, and surgical program. Computer vision can identify procedural stages, extreme effects, anatomical landmarks, and technical knowledge, with possible uses in support and quality assessment (Altememi et al, 2026). AI-based robotics can improve accuracy and navigation, but there is inconsistent evidence for improved outcomes over traditional methods (Altememi et al, 2026). Complications, mortality, and length of stay may be predicted by preoperative models, while postoperative tools are widely used to assess wounds, detecting complication early on, and prediction of infection. Overall, surgical AI is clinically mature. Most of the studies are growing and stronger validation is required before wider claims to justify improvement.

Genomics and Precision Medicine

Modular and genomic datasets are complex and too large only for traditional analysis and AI has been highly needed in precision medicine. Deep learning methods have improved variant for interpreting variant and sequencing data (Boussi Rahmouni et al, 2025). AI models can infer molecular characteristics and response after treatment from histopathology and tumor data in oncology (Boussi Rahmouni et al, 2025). These approaches may not be dependent much on costly testing in some environments, even though there is a need for wider validation. Models can predict extreme reactions and personalized dosing of medications in pharmacogenomics. For instance, dosing based on machine learning has been better in standard models (El Arab et al, 2025). Additionally, AI can predict interactions between medication and medication, identifying high-risk medications and pharmacovigilance. Drug discovery is another area which is expanding significantly, while AI being widely used in optimizing leads, identifying targets, and forecasting clinical trials. Unlike risk forecasting and imaging, clinical effects are not much mature from these applications.

AI in Mental Health

AI can detect symptoms of depression, predict suicide risk, personalize psychotherapy, and identify risks related to psychosis. NLP is widely used to detect undocumented anxiety and depression, while passive sensor and smartphone data is used in digital phenotyping to conclude mental and behavioural

conditions. Gaps in access to care can be filled by these applications, while also escalating unusual concerns about surveillance, privacy, validity, and consent (Pérez-Sanpablo et al, 2025). Both ethical sensitivity and possible reach of AI are illustrated in this area to deploy the same in vulnerable areas.

4.4.Challenges with Healthcare Data Analytics

Data Quality and Privacy

Healthcare AI depends widely on wholeness, quality, and representation of training data. Patient data are incoherently coded, incomplete, and affected by variable documents, which can introduce false relationships and reliability of the model (Pérez-Sanpablo et al, 2025). Data cleaning, standard variable, and preprocessing of data are important instead of secondary levels of developing model. Privacy control also affects AI research across institutions and data sharing. Even though such precautionary measures are needed, it becomes challenging to accumulate different datasets. Federated learning has been a promising avenue for training models without having to centralize data (El Arab et al, 2025). Another major issue is interoperability. Adopting standards may provide more scalable use of AI in clinical areas but progress may be limited by traditional systems (Boussi Rahmouni et al, 2025).

Biased Models

Biased algorithms may amplify existing problems or reproduce false data. As past data is used to train AI models, patterns may be shaped by uneven access to care, structural bias, and discrepant treatment. When training data contains biased information, it may be scaled by AI models. Commercial model used for forecasting healthcare needs undervalued burden of illness in patients of colour rather than White patients with similar severity of illness (Naderian et al, 2025). It defines how structural biases can be encoded by neural design choices apparently. Fairness-aware model should be designed to address those biases (Leivaditis et al, 2025). AI needs wider representation around gender, age group, socioeconomic status, gender, disability, and geography as systems may not generalize to poor population when they are trained in academic environments.

Explainability and Limited Interpretability

In several DL models, a major challenge is limited interpretability for healthcare applications. Healthcare providers have to communicate with patients, justify decisions, and detect errors in suggestions, which are challenging when black box models are applied (Tabassum et al, 2025). Explainable AI models like concept-oriented justifications, attention mapping, and values have been introduced to offer knowledge on model behaviour (Crider et al, 2022). However, there are imperfect approaches and their usability is still a matter of debate as explanations may not explain actual process of decision in the model. More

complex approaches may improve prediction, but simpler models may be preferred in context of high-risk situations.

Regulatory constraints

For clinical AI, regulatory frameworks are being evolved without full adoption to learning systems where performance may vary (Uwimana et al, 2025). Traditional processes were introduced for static devices to use adaptive approaches. There is challenge in resolving medico-legal liabilities. In case of damage due to AI, it may be challenging to assign responsibilities among developers, clinicians, and healthcare organizations (Altememi et al, 2026). Similarly, when AI suggestion is rejected by clinicians, concerns may arise whether such suggestions fall under standards. These uncertainties are major challenge.

Workflow Integration and Trust

Successful adoption of AI relies both on clinical acceptance and technical accuracy to improve workflows in real-world. Trust comes with agreement, transparency, previous experience, and credibility of the developer and program (Higgins and Wilson, 2025). At its core, human factors are very important. Algorithmic bias may cause overdependence of clinicians on AI for suggestions, while ignorance may cause clinicians to avoid useful advice (El Arab et al, 2025). Implementation is also delayed due to alert fatigue, especially when constant false alarms are triggered. Hence, actual efficiency relies on timing, overall design, alignment with routines, and usability.

Ethical concerns

There are several ethical concerns raised about the use of healthcare AI, which are not limited to technicalities. Some of those concerns are informed consent, autonomy of the patient, distributive justice, accountability, and maintaining relationship. Patients may want to know whether decisions are influenced by AI, still there is a need to develop practical standards for consent and disclosure (Hu et al, 2025). Increasing dependence on algorithms could also affect empathy, narrative building, trust, and care in clinical settings (Almagharbeh et al, 2025). Meanwhile, accountability may be limited by proprietary systems to further complicate ethical decision-making (Sharma et al, 2022).

5. Ensuring Accountability with AI in Healthcare System

To describe the use of AI in healthcare for accountability, AI models are tested with recall, F1-score, accuracy, precision, and ROC-AUC instead of depending on accuracy only. This section will help detect false negatives and false positives, including readmitted patients. The model performance was compared across various groups of patients like race and gender. It enables possible differences in the capability of the model to detect patients with high risk instead of assuming equal application of overall performance for all patients. We ensured comparison

of predictions made by AI on actual outcomes. Hence, AI is considered as a tool for decision-making instead of autonomous decision-making.

5.1. Predicting Diabetes Readmission with AI

A publicly available dataset “Diabetes 130-US Hospitals” was used, which consists of data related to hospital encounters from 130 hospitals in the US from 1999 to 2008. The dataset consists of variables like clinical outcomes, demographics, medication, and healthcare usage. This dataset is selected because it is helpful to determine the use of ML models to predict readmission of patients. There is total 101,766 encounters in the dataset, which provides details like gender, age, race, hospital stay duration, admission, number of lab processes, diagnoses, medications, medication use, emergency and outpatient care, etc. The readmitted outcome variable consists of three categories – after 30 days (>30), within 30 days (<30), and non-readmission (NO).

The outcome was transformed into binary problem of classification. In this section, = <30 patients were categorized as positive, which means patients who were readmitted in the hospital in 30 days, while NO and >30 categories were negative ones. This way, AI model can address the problem of decision-support. It can help detect patients who may need follow-up and more monitoring after discharge from the hospital.

5.2. Distribution of Readmission

There was total 101,766 hospital encounters of diabetic patients used in empirical analysis. The original result of readmission was transformed into binary numbers, where coding was done. Code 1 was given to <30 readmission and code 0 was given to both >30 and NO classification. This way, NO readmission had 90,409 (88.84%) encounters and 30-day readmissions had 11,357 (11.16%) encounters (Figure 4).



Figure 4 – Classification of 30-day and No 30-day readmission

There was a significant mismatch in class with very few positive cases. This finding is helpful to determine accountability in healthcare system with AI. Even when a model shows poor performance to detect patients at risk, this finding will still be helpful to determine accountability in healthcare as high accuracy can still be achieved. Hence, apart from accuracy, AUC between precision and recall, ROC-AUC, F1-score, recall, and precision were used.

5.3. Predictive Efficiency

This study is based on two ML models – Random Forest (RF) and Logistic Regression (LR). RF is considered as a collaborative non-linear model and LR is considered as baseline. The data partition was used as patient level to avoid distribution of encounters related to one patient between testing and training datasets. Possible leakage of data is reduced with this approach and it delivers more traditional estimate to generalize the model. Table 1 compares accuracy, recall, precision, F1-score, PR-AUC and ROC-AUC between LR and RF models.

Table 1 – Comparison between Logistic Regression and Random Forest models

Models	Precision	Accuracy	F1-score	Recall	PR-AUC	ROC-AUC
RF	17.29%	71.74%	24.76%	43.56%	0.184	0.636
LR	16.09%	66.94%	24.31%	49.74%	0.181	0.633

The overall accuracy was found higher in RF (71.74%) as compared to LR (66.94%) and F1-score attained was a bit higher. The LR had lower ROC-AUC (0.633) than RF (0.636). However, as compared to RF (43.56%), recall was higher in LR (49.74%). This difference is clear in terms of healthcare as recall shows the number of readmissions that the model identifies. Hence, it is observed that the accuracy and differentiation capability were found higher in Random Forest, while number of high-risk patients was higher in Logistic Regression. The predictive performance was not strong in any of those models that could be deployed in decision-making in healthcare. Rather, it is found that AI-based assessment of risk is feasible while there is a need to further optimize and validate findings.

5.4. Analyzing Prediction and Performance

The 13,521 encounters of NO readmission were classified correctly and there were 937 encounters of 30-day readmission in the test. The 4,481 encounters were classified “non-readmission” wrongly and considered high-risk and couldn’t detect 1,214 encounters which caused readmission in 30 days (Table 2).

Table 2 – Comparison of RF prediction in non-readmission and 30-day readmission

Outcomes in Random Forest	Non-readmission	30-day readmission

Realistic readmission for 30 days	1,214	937
Real non-readmission	13,521	4,481

A lot of false negatives have suggested major limitation from the point of view of accountability. Patient who was readmitted after 30 days was predicted with false negative but was not detected as high-risk by the model. Due to those errors, patients didn't get care or further follow-up in the actual implementation of healthcare. Hence, effects of various kinds of errors related to prediction must be considered by evaluating model instead of curing all errors related to classification similar.

5.5.Explainability and Importance

Previous use of inpatient care was found as the most important model predictor by the RF analysis. Table 3 illustrates the most significant 15 variables.

Table 3 – Most Influential RF variables

Ranks	Forecasting	Relative Value
1	No. of past visits	0.232
2.	Total medications	0.069
3	No. of lab tests	0.065
4	Hospital stays	0.060
5	Age group	0.049
6	No. of ER visits	0.046
7	Total diagnoses	0.046
8	Total procedures	0.033
9	Total outpatient visits	0.024
10	Type of admission	0.022
11	Source of admission	0.020
12	No insulin	0.013
13	Respiratory diagnosis	0.011
14	Circulatory diagnosis	0.010

15	Male patients	0.010
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As compared to other predictor variables, previous use of inpatient care was significantly more impactful, accounting for around 23.2% of total significance of RF. It means significant data can be provided by history of inpatient care to detect future risk related to readmission. Other significant variables are stay duration, burden of medication, lab processes, previous use of emergency, and age. When it comes to accountability, feature value is used to analyze the model behavior. Instead of generating unsolved forecasting, the healthcare features and patient characteristics are important for classification of risks. However, causality cannot be the evidence of feature importance. Readmission risk could not be reduced by changing the important variable for the model.

5.6.Analyzing Fairness of AI Models

The forecasting related to RF was analyzed individually by age group, race, and gender to determine the consistent performance of the model around different groups of patients. The analysis is based especially on recall as false-negative outcome is clinically significant to identify readmitted patient. Table 4 outlines groups of patients with their test encounters, precision, accuracy, and recall.

Table 4 – Prediction of Patient Groups based on Gender and Race

Group of patients	Tests	Accuracy	Precision	Recall
Male	9,280	72.98%	17.93%	42.56%
Female	10,871	70.68%	16.81%	44.43%
Caucasian	15,089	71.17%	17.20%	43.91%
African American	3,847	71.41%	17.58%	43.06%
Asian	125	73.60%	25%	36.84%
Hispanic	393	78.37%	17.86%	48.39%

Other	289	82.70%	25.58%	37.93 %
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Male patients had slightly smaller recall (42.56%) than female counterparts (44.43%) in the model. Caucasians (43.91%) and African Americans (43.06%) had pretty similar recall in racial group of patients. However, recall was comparatively lower for Asians and other groups, i.e., 36.84% and 37.93%, respectively. There is a need to interpret these changes carefully as observations were significantly fewer than larger groups among Asian and other groups. To make AI accountable, model accuracy is not sufficient. Overall performance was acceptable when generating various levels of protection against missed cases among patients. Hence, consistent monitoring is needed for subgroup analysis before using AI models for decision-making.

5.7.Implications for Accountability

With empirical findings, it is observed that patterns related to hospital readmission after 30 days among diabetic patients can be identified by AI. Even though AI can predict readmissions, it is not sufficient for ensuring accountability. The ROC-AUC was 0.636 and accuracy was 71.74% in RF model, while 43.56% was recall for readmission in 30 days. Overall accuracy was lower in LR and recall was higher, i.e., 49.74%. In this study, there is a trade-off between the potential of detecting positive cases and overall performance related to classification.

The value of interpretability is further analyzed by determining feature value. Burden of medication, inpatient usage, hospital stay duration, lab processes, and past use of ER care were some of the most important factors to determine accountability. Those details would be helpful to healthcare practitioners to know the foundation of risk assessment and a point to review specific predictions. Accountable AI is also needed with fairness analysis. Even though overall performance of the model was widely similar between female and male patients and differences were seen among smaller groups.

Instead of showing biasness, findings of the study recommend validation and subgroup tracking before deploying the same. Overall, AI can be used a tool to help healthcare professionals in decision-making to ensure accountability. It is recommended to consider explainability, predictive assessment, review errors related to prediction, and subgroup equality. It matches the concerns observed related to bias, decision-making, human monitoring, and interpretability.

6. Discussion and Conclusion

Algorithmic discrimination has been one of the major challenges for healthcare AI. It has a direct impact on both patient safety and fairness. It is found

that AI models can lead to uneven structure when there is uneven access to biased treatment, proxy systems, and access to care due to training data. Along with diverse datasets, something more is needed to address this concern, such as, developing fairness-aware model, auditing subgroup, and governance systems which track performance related to equity when being deployed. Equity must be considered as a core criterion for performance instead of considering ethics.

Another major challenge is interpretability. Even though predictive efficiency is stronger in highly complex models, their opacity can make accountability complex, affect trust among clinicians, and minimize the potential to detect false positives and false negatives. The question is not accuracy, instead the question is sensible adoption of outputs in decision-making. Overall, AI could be used to transform decision-making in healthcare in all stages like delivery of healthcare, diagnosis, and optimizing prediction of illnesses and treatment. In this study, it is observed that AI models can deliver excellent results in some areas like more efficient and precise care of patients.

However, there is a complex range of regulatory, ethical, and technical challenges to overcome to achieve full potential of AI in ensuring accountability in healthcare, along with technical innovation. There is a need to incorporate data science, clinical experience, implementation, and regulations. To achieve the same, future studies should look at more than assessing workflow and technical performance only. Efficient adoption of AI also relies on preparing healthcare institutions and workforce. Healthcare education should also cover AI awareness, ethical use of AI, regulatory compliance, and practical skills. Along with using AI tools, healthcare institutions are also expected to decide whether they should rely completely on artificial outputs.

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