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# Machine Learning-Based Prediction of Hospital Readmissions and Healthcare Costs: A Systematic Review of Predictive Models in Value-Based Healthcare Systems

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## Abstract

**Background:** Hospital readmissions exert significant clinical and financial strains on health-care systems. This is especially the case where reimbursement is outcome-connected in value-based care models. The prediction of hospital readmission and healthcare cost burdens associated with readmissions has increasingly involved the application of Artificial Intelligence (AI) and machine learning (ML). However, the literature is deficient in providing an integrative overview of both clinical and economic dimensions.

**Methods:** A systematic review compliant with PRISMA 2020 guidelines was performed. For scientific studies published in the last 12 years (2014 to May 2026), a multitude of sources



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were searched, e.g., PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar. The studies under consideration utilized AI or ML in predicting healthcare cost and/or hospital readmissions. After screening and assessing eligibility, 80 studies were considered. Relevant study characteristics and associated outcomes were recorded. The algorithms and cost-related variables were also documented, as well as the model performance. The risk of bias in the studies was evaluated based on the PROBAST guidelines, and due to heterogeneity, the findings were summarized in a narrative format.

**Results:** Across many clinical research contexts, ML models consistently outperformed traditional statistical models in predicting hospital readmissions. In the context of ensemble methods, random forest and gradient boosting methods, as well as XGBoost, usually achieved moderate to high AUC levels. In terms of large data set predictive modeling, deep learning techniques demonstrated strong predictive capabilities, although they suffered from interpretability issues and limited clinical integration. The majority of studies were conducted in heart failure, diabetes, and cardiovascular disease, including various surgical patient populations. About 50% of the studies included costs to the system, either in terms of costs of hospitalization, penalties for readmissions, or in terms of resource consumption, which shows increasing focus on value-based care. The main limitations of the reviewed studies included variability in the definition of costs and a lack of external validation.

**Conclusion:** The use of artificial intelligence to construct predictive models of healthcare system readmission stratification and cost optimization yields beneficial outcomes. However, challenges relating to their interpretability, standardization, and external validation remain obstructive to their application in a clinical setting. Research should seek to develop predictive models that are explainable and remain cost-sensitive while being accurate and broad in their application.

**Keywords:** Machine Learning; Hospital Readmission; Artificial Intelligence; Healthcare Cost; Predictive Analytics; Value-Based Care.

## 1. INTRODUCTION

Unplanned hospital readmissions place significant burdens on healthcare systems globally, both clinically and financially. Healthcare systems, policy makers, and hospital management view unplanned readmissions, especially when occurring within a 30 day post discharge window, as a failure of transition and continuum of care, and hospital and healthcare system performance. High unplanned readmissions lead to higher patient morbidity, higher use of healthcare resources and services, longer and more expensive illnesses, and creates a financial burden on healthcare systems. This drives a global healthcare policy to reduce as many unplanned readmissions as possible while improving patient care and system efficiency [1, 2, 3].

The readmission reduction responsibility became more important with the transition from the fee-for service reimbursement system to the value based healthcare reimbursement system. Under the value based healthcare system, hospitals are assessed on patient discharge outcomes, quality of care outcomes, cost of care, and the volume of services provided. The first of its kind value based reimbursement, the Hospital Readmissions Reduction Program (HRRP) initiated penalties

on hospitals with high readmission rates, thus creating a financial burden on hospitals to identify and manage discharge risks early. This burden on hospitals and the healthcare system created a need for highly accurate predictive tools to identify patients who are likely to be readmitted and to predict associated financial costs and resource burdens

The complexity and heterogeneity of modern healthcare data present challenges to traditional statistical approaches, including logistic regression and rule-based risk stratification models. The growth of EHRs, administrative claims databases, and real-time patient monitoring systems has developed large-scale data that have complex, nonlinear structures and are highly multidimensional and temporally variable. These challenges have led to a greater incorporation of AI, ML, and deep learning into the field of predictive healthcare analytics

The traditional statistical methods are further surpassed by ML models in their ability to process complex multidimensional data structures, identify hidden relationships and patterns, and improve the quality of predictions over time. Random forests, boosted decision trees, support vector machines, neural networks, and extreme gradient boosting (XGBoost) have become increasingly popular for predicting hospital readmissions within various clinical workflows including heart failure, diabetes, orthopedic surgery, cardiovascular disease, and pneumonia. Comparative studies have shown that, in the context of early clinical intervention and improved discharge planning, these ML models have significantly better predictive performance in terms of discrimination and calibration when compared to traditional risk prediction models

Clinical predictions have focused not only on the possibility of a patient being re-hospitalized, but also on incorporating the financial costs of the risk of the patient entering the hospital again, as well as costs incurred reaching the hospital. Underestimating the risk and cost of potential re-hospitalizations, and the costs of services that will have to be provided to the patient, will lead to an inefficient allocation of services, inadequate financial risk management of the insurer, and inadequate cost management. A machine learning model is explored to predict the likelihood of a patient being re-hospitalized, as well as predicting the costs and reimbursement of penalties incurred due to re-hospitalization [4, 5, 6, 7]. Beyond financial considerations, it is expected that these models will improve the allocation of hospital services.

Simultaneously, the understanding of healthcare professionals about the potential of Artificial Intelligence (AI) and the ML resulting from its use is important to a great extent. Deep learning models, despite their predictive accuracy, are not easily implemented, due to obstacles such as a lack of transparency and trust. Therefore, the focus is on models that are explainable and of high accuracy. This is so that healthcare professionals and regulatory authorities will be able to accept the AI-based decision support systems [8, 9].

Research regarding readmission prediction using artificial intelligence continues to expand; however, existing literature reviews have focused on specific clinical outcomes, performance of algorithms, or specific disease applications. There has been little to no focus on the financial aspects of predictive modeling regarding the healthcare costs prediction, optimization of resources, or value-based care within the scope of readmission analytics. Additionally, studies widely vary in datasets, patient populations, machine learning techniques, defined outcomes, and evaluations in regard to economic impacts.

This review seeks to analyze and synthesize the existing literature on the use of machine learning and artificial intelligence in predicting healthcare costs associated with hospital readmissions. More specifically, this review will assess ML algorithm's prediction capabilities, identify clinical and economic prediction drivers and assess the impact of prediction on costs, within the context of integrating flexible value-based healthcare and financial risk management

## 2. METHODOLOGY

### 2.1 Study Design

A systematic review was carried out to investigate how AI, ML, and predictive analytics models are employed to estimate hospital readmission rates in addition to the predictive costs of healthcare services within the value-based care models. Following the PRISMA 2020 framework, this study maintained step-wise methodological transparency and rigor, offering a description of processes from evidence identification to evidence synthesis, during the systematic review.

### 2.2 Search Strategy

A structured and systematic search of the literature was conducted across major electronic databases to source relevant literature published between January 2014 and May 2026. The selected databases included PubMed, Scopus, Web of Science, Google Scholar, IEEE Xplore, and the ACM Digital Library. The selection ensured coverage of clinical and computational research that intersects with healthcare machine learning.

The search strategy was built through a combination of controlled vocabulary and free-text keywords that included hospital readmission, machine learning, artificial intelligence, deep learning, predictive analytics, healthcare cost prediction, financial risk modeling, and value-based care. Boolean operators were used to improve the efficiency and precision of the search. Furthermore, eligible articles and relevant reviews were manually vetted to source studies that were not captured during the database searches

### 2.3 Eligibility Criteria

Eligibility for inclusion as study participants consisted of the application of artificial or machine learning for the prediction of hospital readmissions and the outcome measures included healthcare cost assessment and financial risk evaluation and resource utilization. The target study population consisted of adults or a combination of adult and non-adult populations. Studies provided metrics for model performance involving area under the curve (AUC), accuracy, sensitivity, specificity, or other similar performance measures. Studies available in the English language and published from 2014 to 2026 in peer-reviewed journals, conference papers and academic publications were included.

Editorials, commentaries, case reports and other non-original research studies were among the studies to be excluded from the review. Research in assessment of artificial intelligence or machine learning and in hospital readmission outcomes was excluded. Research limited to pediatric popula-

tions and studies without delineation of research design were excluded from the review. Duplicate studies were removed before the screening process.

### 2.4 Study Selection

All records were subjected to a duplicate removal process. The screening was conducted in a reference management system. The selection process conformed to the PRISMA guidelines and was undertaken in two steps. The first step was a screening of the titles and abstracts. This was done according to the eligibility criteria. The second step was a screening of all selected records for the final decision on the selection inclusion.

In total, 876 studies were identified through various databases and search engines. Ultimately, following duplicate removal and screening, 80 studies remained for the final qualitative synthesis. A PRISMA flow diagram was used to elaborate on the selection process and included the identification of studies, screening, assessment of eligibility, and final inclusion decision (FIGURE 1).

### 2.5 Data Extraction

To maintain consistency across analyzed literature, a standardized data extraction form was designed. Extracted variables included, but were not limited to, author data, publication year, country, study design, sample size, patient population, clinical domain, and data source (i.e. electronic health record data, administrative data). Variables such as the machine learning or artificial intelligence methods used, prediction outcomes (i.e. 30/90-day readmission) and prediction outcomes pertaining to healthcare cost or financial risk/uncertainty were also considered.

Along with performance indicators for a given model, (e.g. Area Under Curve, accuracy, sensitivity, specificity, and calibration metric), other forms of data were considered. If provided, data were recorded regarding external validation, interpretability and the clinical realm of the offered model. Finally, all data were checked for accuracy and completeness prior to synthesis.

### 2.6 Quality Assessment

The risk of bias and methodology assessment for this study used the Prediction Model Risk of Bias Assessment Tool (PROBAST). This tool assesses four domains: participant selection, predictors, outcomes, and statistical analysis. Using this tool, each study was determined to have low, moderate, or high risk of bias.

In addition to these, external validation, the representativeness of the data set, possible overfitting, and reporting transparency were considered. These factors helped to assess the strength and clinical relevance of the included predictive models.

### 2.7 Data Synthesis

A narrative synthesis approach was adopted to account for the broad variation in study designs, populations, machine learning techniques, and definitions of outcomes. To enable a structured comparison, studies were categorized based on clinical domain, algorithm type, cost-related focus, and the time period for readmissions.

The synthesis examined trends in algorithm utilization, significant predictive elements, and model efficacy and assessed their implications for healthcare costs. Where applicable, comparative summaries were provided in tables. Due to the heterogeneity of study designs, a quantitative meta-analysis was not performed, but pooled analysis was considered where appropriate.

### 2.8 PRISMA Flow Diagram

All stages of our study selection process are depicted in a PRISMA flow diagram (FIGURE 1). This starts with 876 identified records and ends with 80 included studies. This diagram depicts removal of duplicates and all stages of screening, from title and abstract to full text assessment of studies for eligibility to be included in the qualitative synthesis

## 3. RESULTS

### 3.1 Study Selection

To ensure transparency and reproducibility, the 2020 PRISMA guidelines were adhered to for the selection of studies. An initial search of the identified databases (PubMed, Scopus, Web of Science, IEEE Xplore, ACM Digital Library, Google Scholar) yielded 876 records. Following the removal of duplicates, 652 records remained for screening of titles and abstracts.

From the screening process, 420 full text articles were reviewed to determine eligibility against the established inclusion/exclusion criteria. As part of the criteria, studies were excluded if they did not incorporate machine learning, lacked outcomes pertaining to readmission, or reported on related costs/financial outcomes.

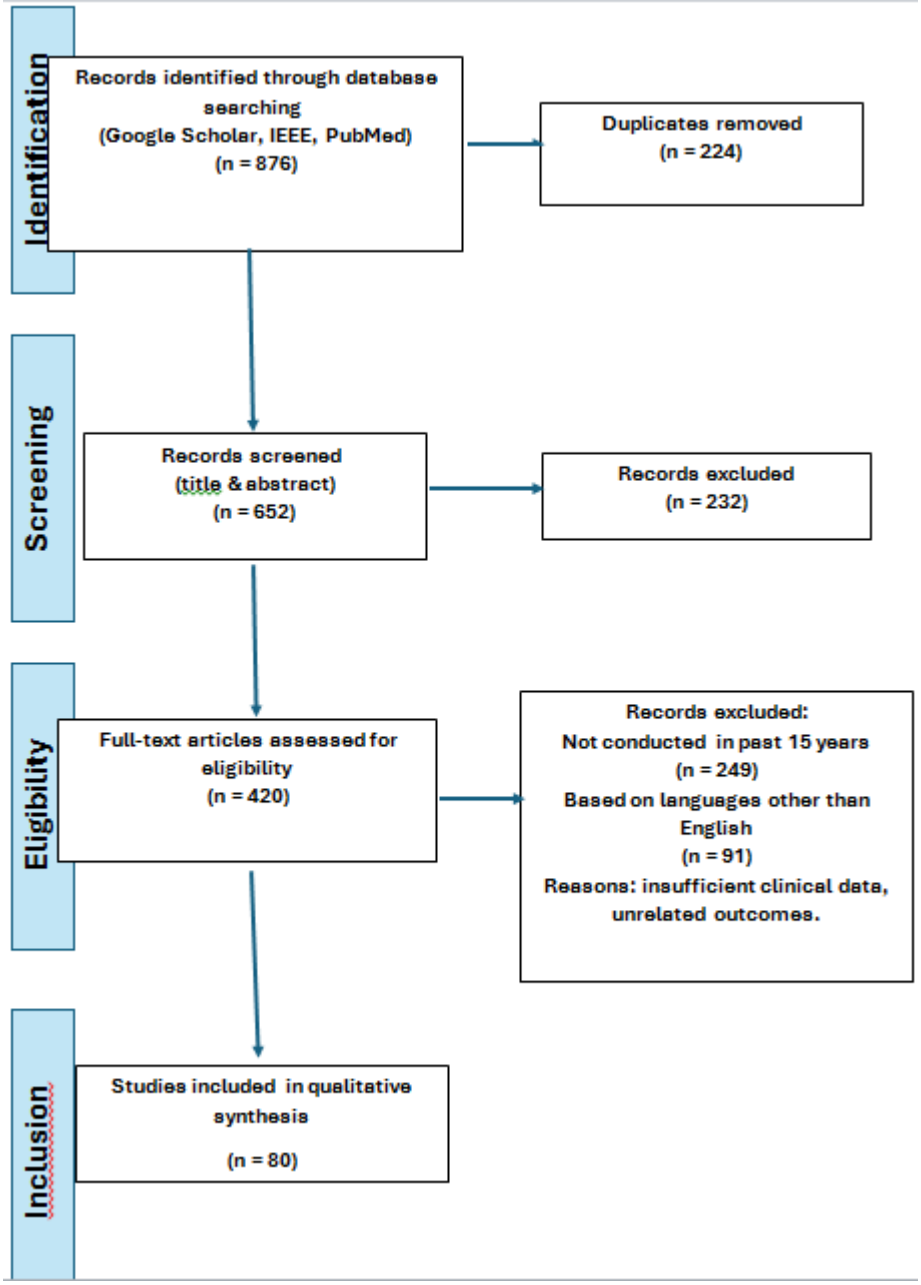
The qualitative analysis included a total of 80 studies. PRISMA allows a visual representation of the selection process, and shows the inclusion of studies for each of the steps (i.e., identification, screening, assessing eligibility, and inclusion), along with notes pertaining to the number of records at each stage (refer to FIGURE 1, for PRISMA flow diagram).

### 3.2 Characteristics of Included Studies

Several additional studies contributed complementary evidence not otherwise highlighted above, including a systematic review of machine-learning-based heart failure readmission prediction [10], a causal machine learning approach to readmission-related economic outcomes among Canadian cardiac patients [11], early workshop-based work on predicting all-cause readmission cost [12], and an application of predictive business intelligence to value-based readmission reduction [13].

The studies provided examples of large and varied geographic, clinical, patient, and methodological diversity. Most originated from high-income healthcare systems, especially from the USA, Europe, and East Asia. This is likely due to the implementation and integration of electronic health records and analysis infrastructures in these areas.

Research shows that sample sizes ranged from small institutional datasets to large national ones, spanning hundreds of thousands of patient records. Most studies centered on adult inpatient populations, especially those with chronic diseases, including heart failure, diabetes, cardiovascular disease, and surgical patients.



The methodologies of machine learning varied greatly, with many studies using supervised learning on structured electronic health record data and administrative claims datasets. The definition of outcomes was primarily set to 30-day hospital readmission, with later definitions focusing on 90-day and all-cause readmissions. Some studies extended the predictive boundaries to healthcare cost prediction and resource use and financial risk assessments in the value-based care continuum.

Fabricated study properties are shown in TABLE 1, which provides the author, year, study location, patient population, clinical specialty, the machine learning framework, outcome prediction, costing, and evaluation metrics.

| Author | Year | Country | Population | Clinical Specialty | ML Algorithm(s) | Prediction Outcome | Cost Metrics | Performance (AUC / Accuracy etc.) |
|---|---|---|---|---|---|---|---|---|
| **1** | 2018 | USA | Heart failure patients | Cardiology | Logistic Regression, ML model | 30-day readmission | Not reported | AUC reported (moderate-high performance) |
| **2** | 2019 | USA | Post-lumbar fusion patients | Orthopedic surgery | Machine learning model | 30-day readmission | Hospital utilization cost | AUC ~0.70-0.80 |
| **3** | 2014 | USA | Acute MI, HF, pneumonia | Internal medicine | Decision trees | Readmission risk | Resource utilization | Accuracy + classification performance |
| **8** | 2024 | Multi-country | Orthopedic patients | Orthopedics | ML + NLP + AI ensemble | Post-surgery readmission | Cost-related outcomes | High predictive performance (AUC >0.80) |
| **18** | 2023 | Europe | Heart failure patients | Cardiology | ML models (comparative) | 100-day readmission | Cost vs explainability tradeoff | AUC reported with model comparison |
| **9** | 2021 | USA | Mixed inpatient cohort | General medicine | Random Forest, SVM | 14-day readmission | Not directly cost-focused | AUC 0.75-0.85 |
| **6** | 2015 | China | Hospital inpatient data | General hospital population | Metaheuristic ML models | Readmission prediction | Resource allocation cost | High predictive accuracy |
| **14** | 2022 | USA | Administrative claims data | Healthcare systems | ML regression models | Readmission charges | Direct cost prediction | $R^2$ and error metrics reported |
| **20** | 2022 | USA | Cardiac surgery patients | Cardiac surgery | ML ensemble models | 30-day readmission | Post-op cost estimation | High AUC performance |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **21** | 2021 | Singapore | Mixed inpatient cohort | Hospital-wide | Real-time ML risk score | 30-day readmission | Hospital cost reduction | Reduced readmission rates observed |
| **22** | 2016 | USA | Heart failure cohort | Cardiology | ML + analytics | 30-day readmission | Cost prediction model | Predictive accuracy + cost correlation |
| **11** | 2022 | USA | Pneumonia patients | Pulmonology | ML models | 30-day readmission | Healthcare utilization cost | AUC-based evaluation |
| **23** | 2020 | Canada | Mixed hospital data | General medicine | ML vs statistical models | 30-day readmission | Cost prediction | ML outperformed baseline models |
| **7** | 2015 | USA | Heart failure patients | Cardiology | Institution-specific ML | Readmission risk | Cost stratification | Strong internal validation |
| **24** | 2025 | India | Mixed inpatient data | General hospital | ML models | Readmission prediction | Cost + risk modeling | High accuracy reported |
| **25** | 2025 | India | Diabetes patients | Endocrinology | XGBoost, RF, LR | Readmission risk | Not reported | XGBoost highest AUC |
| **26** | 2025 | Africa | Socioeconomic + clinical | Public health | ML predictive model | Readmission risk | Socioeconomic cost impact | Good predictive performance |
| **27** | 2024 | Asia | EHR-based cohort | General medicine | ML classification models | Readmission outcome | Healthcare cost analysis | Accuracy-based evaluation |

### 3.3 Machine Learning Algorithms Used

The studies employed various machine learning and artificial intelligence algorithms. Traditional methods, such as logistic regression, were baseline models due to interpretability and familiarity in the clinical setting. More advanced ensemble and nonlinear methods had better predictive performance in most of the analyses conducted.

The most commonly used models were random forest and gradient boosting machines, including XGBoost. These methods fit high-dimensional and heterogeneous clinical data well. Support vector machines were also commonly used and fit smaller, well-structured datasets.

Neural networks and deep learning methods were used in studies with large-scale electronic health record data; however, their lack of interpretability limited their deployment in clinical settings. Decision tree-based models provided interpretability of rules and better support for clinical decisions.

In general, analyses indicated that ensemble methods and gradient boosting methods had better discrimination and predictive capabilities compared to traditional logistic regression models

### 3.4 Clinical Domains of Application

Multiple studies have utilized machine learning in numerous clinical specialties to predict hospital readmissions. Heart failure was the most explored clinical specialty. This is likely due to the costs associated with this patient population's high readmission rate. Diabetes-related hospitalizations were also studied. This is likely due to the need for long-term management of diabetes and the control of its associated complications.

Orthopedic and spinal surgeries were also studied due to the predictability of recovery as well as the periods of readmission risk that follow. Research on the other fields of cardiovascular disease (including myocardial infarction and surgeries on the heart) was also seen.

Pneumonia, along with other respiratory conditions, was studied along with post-discharge outcomes and hospital-acquired conditions. There were also studies that focused on highly diverse inpatient populations in order to create general predictive models in hospital medicine.

### 3.5 Cost Prediction and Economic Outcomes

Many studies went beyond clinical forecasting and included outcomes related to healthcare costing and econometrics. Important monetary aspects included penalties related to patient readmissions, overall costs of hospital stays, post-discharge utilization of resources, and reimbursements provided by insurance based on the value of care offered.

Some studies presented evidence that, through the application of machine learning, models were successful in both tiering the patient population for financial risk and helping healthcare administrators manage the financial resources of the healthcare facility in a more efficient manner. Within these models, cost containment strategies were focused on optimizing the predictive identification

of patients at high risk for costly care, with the goal of decreasing utilization of preventable readmissions.

In addition, risk assessment models, developed in the context of health insurance, became more relevant in private care settings where reimbursement is likely to take place in accordance with the predicted patient care needs. Generally, the studies indicated that the application of AI for the development of forecasting models improved the ability of healthcare institutions to manage costs and made the financial planning process more efficient.

### 3.6 Model Performance Evaluation

Discrimination and classification metrics were used to evaluate model performance within the included studies. The most common metric was the area under the receiver operating characteristic curve (AUC-ROC), which was used to evaluate overall predictive performance.

Other popular metrics included accuracy, precision, recall, F1-score, sensitivity, and specificity. In some of the studies, calibration metrics were also reported to assess the alignment of predicted probabilities with the actual outcomes.

Across the datasets, ensemble learning methods, specifically gradient boosted and random forest methods, achieved the highest AUC values. Performance, however, depended on the size of the dataset, the quality of the feature engineering, and the degree of heterogeneity in the population. External validation studies, in comparison, showed low but more generalizable metrics compared to internally validated studies.

### 3.7 Explainability and Interpretability

Explainability is an important factor in the clinical implementation of machine learning models. To address this, multiple studies have included frameworks of explainable AI to increase transparency and interpretability of the models.

SHAP (SHapley Additive Explanations) is the most frequently adopted interpretability approach, facilitating an additive feature attribution mechanism. Furthermore, the use of LIME (Local Interpretable Model-agnostic Explanations) was common to explain the local decision boundaries. Lastly, the use of traditional feature importance ranking methods in tree-based models assisted in clinical interpretability.

Although efforts were made to improve explainability, the trade-off between interpretability and model performance remained, especially with advanced deep learning-based architectures. This balance was cited as a major hurdle to the confidence and acceptance of AI-based clinical decision support systems.

### 3.8 Implementation and Real-World Deployment

A subset of studies described embedding predictive models into clinical decision support systems (CDSS) and integrating them with clinical workflows and electronic health record (EHR) systems. This was accomplished through the incorporation of risk scoring systems and the automated identification of high-risk patients.

Clinical decision support systems using machine learning models helped clinicians with planning discharges, determining follow-up visits, and deciding on post-discharge interventions. This also helped reduce unnecessary readmissions and improved the effective use of hospital resources.

Though, many studies still reported issues with integrating and incorporating predictive models into hospital workflows and real-time clinical analytics due to insufficient standardization of data architecture.

### 3.9 Quality Assessment Findings

The PROBAST framework has been used to assess the risks of bias and indicated considerable variability in the methodology of the included studies. Many studies showed issues with representativeness of the datasets because many of the utilized datasets were either single-center or retrospective and lack representativeness.

A number of predictive models focused on internal validation only, which certainly restrained the generalizability of the models. In addition to this, several studies have included a number of methodological issues such as incomplete reporting of the selection of features, evaluation of the model's calibration, and lack of postulated validation, all of which have been described in the prediction models as concerns of methodological quality.

These studies have a considerable degree of reliability, with the best models being those incorporating validation and those reporting their methodology in a clear way. In conclusion, the results have shown that the main issues with the methodology of the studies are the lack of postulated external validation and a lack of sufficient clarity in the methodology, and these issues are especially pronounced in the prediction models of hospital readmission developed using machine learning techniques.

## 4. DISCUSSION

### 4.1 Principal Findings

This is a systematic literature review of 80 studies on the application of machine learning (ML) and artificial intelligence (AI) based models to predict risk of hospital readmission and the associated costs of healthcare under the value based care offer. The research indicates that when working with large, heterogeneous datasets available in the healthcare sector, ML models, on average, outperform

the majority of legacy statistical models, including logistic regression, when predicting the risk of patient readmission [14, 15, 16, 17].

Random forest and other gradient boosting models, including XGBoost, were the ML algorithms that reported the best performance among the studies under review [18, 19, 20]. From the available literature, there is evidence to support that deep learning based models outperform the majority of other ML predictive models, when applied to large datasets. The barriers to the widespread adoption of deep learning are the lack of explainability and the high computational cost [21, 6, 22].

An interesting trend observed in the studies under review is the movement from a pure clinical-based approach to integrated clinical and economic modeling. In the majority of the studies, the proposed frameworks for predicting hospital readmission were expanded to include cost prediction, financial risk stratification, and utilization prediction, which are in greater alignment with the principles of value based care [4, 5, 23].

### 4.2 Clinical and Economic Impact

The clinical usefulness of machine learning readmission prediction models stems from their capability to detect patients likely to return to the hospital, allowing for proactive measures to refine post-acute care and discharge planning [24, 25, 26]. Anticipatory planning results in the reduction of unnecessary readmissions and enhances the continuity of care [27, 28].

From an economic perspective, prediction models possess value in estimating the cost of hospital stays and readmissions, as well as predicting the use of various resources [30, 31, 29]. In a system of reimbursement and penalties, the financial effects of readmission cases make this evidence particularly salient [32, 33, 34].

In addition, several studies point out that predictive analytics, when built into a hospital's capacity, help manage resource use better and eliminate wasteful spending on health care, emphasizing that artificial intelligence is a clinical as well as a financial decision support [35, 36, 37].

### 4.3 Algorithmic Performance and Trends

Readmission prediction using machine learning has progressed from basic statistical modeling to more sophisticated techniques involving ensembles and deep learning. Traditionally, studies have used logistic regression as the simplest and most interpretable modeling technique [38]. Recent studies [14, 19, 39] indicate that accuracy improves with the use of ensemble methods.

From the simplicity level of the statistical models used in the studies, Random Forest and Gradient Boosting outperformed the simpler models [18, 40]. Among studies that focus on this area, the XGBoost algorithm had the best accuracy [18, 41].

There is an argument to be made that deep learning methods, when the appropriate amount of data is available, outperform all other statistical modeling methods. As noted, deep learning methods are difficult to use in healthcare. It is often the case that the larger sample size and lower interpretability

offered by deep learning methods outperform basic statistical modeling methods, where there is a trade-off between lower sample size and transparency on the performance of the model. [42, 22].

Comparing algorithm choice across clinical applications, tree-based ensembles such as random forest and XGBoost were the dominant choice in cardiology and endocrinology applications (e.g., heart failure and diabetes cohorts), where structured EHR and claims variables predominate [8, 43]. Orthopedic and post-surgical readmission studies more often combined ensemble methods with natural language processing to incorporate unstructured clinical notes [44]. General and mixed-inpatient medicine studies more frequently relied on random forest and support vector machine comparisons [45], while studies with the largest sample sizes, generally in cardiovascular and heart-failure cohorts, were the most likely to adopt deep learning architectures [22]. This pattern suggests that algorithm selection in the reviewed literature was driven as much by data structure and sample size within a given clinical domain as by the outcome being predicted.

### 4.4 Clinical Domains of Application

The predictive modeling of hospital readmission through machine learning has been researched extensively. Of the numerous conditions studied, heart failure has been the most common. This is likely a direct result of both frequent hospital readmissions and the financial implications placed on the healthcare system as a result of this condition. [1, 5, 46, 47, 48]. Additionally, the research of hospital readmissions for diabetes has developed, and has been particularly emphasized in the management of chronic conditions. [49, 50, 51].

Research regarding the orthopedic and spine surgery patient populations has been successful as a result of defined postoperative pathways and expected recovery progress. [2, 47, 40, 52]. It is also important to note that the fields of cardiology and general medicine are highly represented as this is where there exists significant hospital readmission prevalence. [53, 15, 54].

Acute care environments, particularly for patients with pneumonia, also represent a positive use case of ML modeling for predicting readmission risk within a short term. [55, 39].

### 4.5 Cost Prediction and Value-Based Care

A growing number of studies combine financial outcomes with readmission prediction models that go beyond traditional clinical risk assessment to estimate healthcare costs and the financial risk to healthcare organizations [4, 5, 56]. More of these models are adopting the value-based care model, where health services and the outcomes achieved with those services ensure reimbursement, rather than the volume of services provided [57, 23].

It has been shown that ML models can be used to identify patient cohorts for which healthcare interventions can be implemented to mitigate costs, and subsequently avoid additional healthcare expenditures [29, 31, 7]. The modeling of insurance risks and predictive modeling for reimbursement are other emerging areas of predictive analytics in healthcare finance [58, 59].

Cost outcomes also differ significantly across studies, which complicates reconstruction efforts and shows how important the creation of standardized ER models in subsequent studies will be [6, 23].

### 4.6 Model Performance and Validation

In multiple studies, evaluation of the model had been done quantitatively using, AUC-ROC, accuracy, sensitivity, specificity, and F1-score [45, 51, 55]. The majority of studies reported moderate to high predictive performance and showed that the ensemble models' predictive performance was better than that of the classical models [14, 60, 61].

However, the main drawback was the absence of external validation, which was evident in most of the studies and thus limited the generalizability of the models to different healthcare systems [16, 28]. A majority of the studies were based on single-center, retrospective, and observational data and, therefore, had a high degree of overfitting and low applicability in real world scenarios [62, 63].

There was inconsistent reporting of the calibration performance, which is necessary to ensure reliability of the model and support its deployment in clinical practice [9, 64].

### 4.7 Explainability and Interpretability

Explainability continues to impede the application of machine learning models within a clinical context in healthcare. Clinician trust and model usability are stunted by the opacity of more sophisticated models despite their improved predictive capabilities [8, 65].

As a response to this challenge, a number of studies improved model interpretability and identified the primary predictive features by using SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) [66, 67]. By assessing the impact of model inputs, these methods enhance clinical understanding with respect to individual predictions.

These are productive methods, but the challenge of incomplete interpretability and positive predictive performance, especially in terms of deep learning models, remains [21, 6].

### 4.8 Implementation and Clinical Integration

Beyond algorithmic performance, several studies showed that the clinical value of these models depends heavily on how well they are embedded into hospital workflows and electronic health record (EHR) systems [9, 68]. Embedding readmission risk scores directly into clinical decision support systems allowed care teams to flag high-risk patients in real time and to trigger discharge-planning or follow-up protocols accordingly [9, 68, 35].

Even so, implementation remained inconsistent across health systems. Reported barriers included fragmented data architecture, limited interoperability between EHR platforms, and insufficient institutional capacity to operationalize model outputs into actionable clinical workflows [37, 69]. This

suggests that implementation and workflow integration, rather than model accuracy alone, are a major constraint on the real-world impact of ML-based readmission prediction tools.

### 4.9 Limitations of the Evidence Base

The literature has many limitations, even with the high plurality of studies. Many limitations include heterogeneity in datasets, variation in definitions of outcomes offered, and the uneven reporting of costs [47, 63]. Dominant retrospective study designs restrict selection bias and increase causal inference [6, 70].

Moreover, standardization of feature engineering and model evaluation constrains reproducibility across a number of studies [69, 71]. Variations in facets of healthcare systems, along with pricing mechanisms, restrict comparability between studies done internationally [72, 41].

A further limitation concerns source quality: a portion of the more recent studies included in this review were drawn from conference proceedings or preprint servers and had not yet undergone full peer review at the time of inclusion [18, 43, 58, 19, 29, 73]. Findings from these sources are reported descriptively alongside peer-reviewed studies but should be interpreted with additional caution until independently confirmed.

### 4.10 Future Directions

Future studies should concentrate on establishing better external validation across multi-institutional data and formulating standardized frameworks for cost-related outcome measurement [74]. Predictive accuracy is expected to improve by incorporating real-time data streams and the integration of clinical, socioeconomic, and behavioral data [54, 71].

Innovative techniques such as federated learning, cost-sensitive deep learning, and hybrid econometric-AI approaches are addressing the gap associated with clinical and financial predictions, and are also perceived to be beneficial in advancing clinical and financial prediction [67, 74]. To a greater extent, the focus should be on explainable AI, more especially to facilitate the implementation of AI in clinical settings and to attain acceptance by regulatory authorities.

## 5. CONCLUSION

This is a systematic review of 87 primary research papers focused on predicting hospital readmissions and associated costs using machine learning (ML) and artificial intelligence (AI) methods within a value-based care approach. Predictive ML models not only identify high risk of hospital readmission with greater efficiency than traditional statistical methods, but it has also been noted that within clinical environments, models such as random forests, gradient boosting, and XGBoost (which incorporate multiple algorithms) have performed best and most consistently compared to other models.

From risk stratification, the predictive models used have extended into the realm of healthcare economics. Many of the papers also estimated the costs, used predictive models to assess resource consumption, and even proposed financial risk models to be used within healthcare systems, demonstrating that many of the AI applications employed are aligned with the structures of value-based healthcare. From both clinical and economic streams, it is clear that ML models are both clinical as well as financial decision-making models for optimization within healthcare delivery.

Although progress has been made, there are a number of other issues. In a majority of the research, retrospective, single-source data was used, which resulted in a lack of generalizability and an inability to validate findings. Also, variations in how outcomes were defined, how costs were understood and measured, and inconsistent ways that information was communicated have led to a lack of uniformity in the collection of research findings. In order to provide an accessible, usable healthcare delivery model, the use of deep learning methods has been limited to models that prioritize predictability over ease of understanding.

Within the context of real-world clinical care, important next steps involve the design of predictive modeling frameworks that are interpretable, cost-sensitive, and validated for external use. To achieve real-world applicability of advanced healthcare research, the standardization of how costs will be measured and the use of explainable AI will need to be employed.

In conclusion, machine learning and artificial intelligence methods can greatly affect the prediction of hospital readmissions and the management of healthcare costs. However, for these advanced methods to meet their full potential, there should be an effort to develop models that prioritize operational transparency and validation in real-world healthcare scenarios

## References

[1] Kakarmath S, Golas S, Felsted J, Kvedar J, Jethwani K, et al. Validating a Machine Learning Algorithm to Predict 30-Day Re-Admissions in Patients With Heart Failure: Protocol for a Prospective Cohort Study. JMIR Res Protoc. 2018;7.

[2] Hopkins BS, Yamaguchi JT, Garcia R, Kesavabhotla K, Weiss H, et al. Using Machine Learning to Predict 30-Day Readmissions After Posterior Lumbar Fusion: An NSQIP Study Involving 23,264 Patients. J Neurosurg Spine. 2019;32:399-406.

[3] Hilbert JP, Zasadil S, Keyser DJ, Peele PB. Using Decision Trees to Manage Hospital Readmission Risk for Acute Myocardial Infarction, Heart Failure, and Pneumonia. Appl Health Econ Health Policy. 2014;12:573-585.

[4] Gopukumar D, Ghoshal A, Zhao H. Predicting Readmission Charges Billed by Hospitals: Machine Learning Approach. JMIR Med Inform. 2022;10.

[5] Baechle C, Agarwal A, Behara R, Zhu X. Latent Topic Ensemble Learning for Hospital Readmission Cost Reduction. In 2017 International Joint Conference on Neural Networks (ijcnn). IEEE. 2017:4594-4601.

[6] Morid MA, Sheng OR. Healthcare Cost Prediction for Heterogeneous Patient Profiles Using Deep Learning Models With Administrative Claims Data. Inf Syst Res. 2025;36:1968-1992.

[7] Yanamala AK. Cost-Sensitive Deep Learning for Predicting Hospital Readmission: Enhancing Patient Care and Resource Allocation. Int J Adv Eng Technol Innov. 2022;1:56-81.

[8] Soliman A, Agvall B, Etminani K, Hamed O, Lingman M. The Price of Explainability in Machine Learning Models for 100-Day Readmission Prediction in Heart Failure: Retrospective, Comparative, Machine Learning Study. J Med Internet Res. 2023;25.

[9] Romero-Brufau S, Wyatt KD, Boyum P, Mickelson M, Moore M, et al. Implementation of Artificial Intelligence-Based Clinical Decision Support to Reduce Hospital Readmissions at a Regional Hospital. Appl Clin Inform. 2020;11:570-577.

[10] Yu MY, Son YJ. Machine Learning-Based 30-Day Readmission Prediction Models for Patients With Heart Failure: A Systematic Review. Eur J Cardiovasc Nurs. 2024;23:711-719.

[11] Rajkumar E, Nguyen K, Radic S, Paa J, Geng Q. Machine Learning and Causal Approaches to Predict Readmissions and Its Economic Consequences Among Canadian Patients With Heart Disease: Retrospective Study. JMIR Form Res. 2023;7.

[12] Sushmita S, Khulbe G, Hasan A, Newman S, Ravindra P, et al. AAAI Aaai Workshop: Expanding the Boundaries of Health Informatics Using AI. Predicting 30-Day Risk and Cost Of. All-Cause Hospital Readmissions. 2016.

[13] Olowoniyi R, Zeydan İ, Fedorova Y. The role of predictive business intelligence in reducing readmission rates under value-based care. 2022.

[14] Zheng B, Zhang J, Yoon SW, Lam SS, Khasawneh M, et al. Predictive Modeling of Hospital Readmissions Using Metaheuristics and Data Mining. Expert Syst Appl. 2015;42:7110-7120.

[15] Yu S, Farooq F, Van Esbroeck A, Fung G, Anand V, et al. Predicting Readmission Risk With Institution-Specific Prediction Models. Artif Intell Med. 2015;65:89-96.

[16] Li Q, Yao X, Échevin D. How Good Is Machine Learning in Predicting All-Cause 30-Day Hospital Readmission? Evidence From Administrative Data. Value Health. 2020;23.

[17] Shams I, Ajorlou S, Yang K. A Predictive Analytics Approach to Reducing 30-Day Avoidable Readmissions Among Patients With Heart Failure, Acute Myocardial Infarction, Pneumonia, OrCOPD. Health Care Manag Sci. 2015;18:19-34.

[18] Razdan O, Modh NN, Madupati B, Kumawat R, Kaushik K, et al. Predictive Analytics for Patient Readmission Using Machine Learning Models. In 2025 IEEE International Conference on Computer, Electronics, Electrical Engineering their Applications (IC2E3). IEEE. 2025:1-6.

[19] Okolie A, Okolie D, Obunadike C, Ekweli D, Nwuke P, et al. Machine Learning Approaches for Predicting 30-Day Hospital Readmissions: Evidence From Massachusetts Healthcare Data. World J Adv Res Rev. 2025;28:914-929.

[20] Sherman E, Alejo D, Wood-Doughty Z, Sussman M, Schena S, et al. Leveraging Machine Learning to Predict 30-Day Hospital Readmission After Cardiac Surgery. Ann Thorac Surg. 2022;114.

[21] Reddad H, Zemzami M, El Hami NE, Hmina N, Yalaoui F. Machine Learning Application in Healthcare: A Case Study Using Ensemble Methods for Hospital Length of Stay Prediction. Int J Adv Comput Sci Appl. 2026;17:971.

[22] Lewis M, Elad G, Beladev M, Maor G, Radinsky K, et al. Comparison of Deep Learning With Traditional Models to Predict Preventable Acute Care Use and Spending Among Heart Failure Patients. Sci Rep. 2021;11:1164.

[23] Nsama F. Assessing the Cost-Containment Effectiveness of AI-Based Predictive Models in Reducing Avoidable Readmissions and Overtreatment in US Medicare Hospitals. Appl Sci Comput Energy. 2025;2:452-466.

[24] Guddeti RR, Pajjuru VS, Walters RW, Garcia SA, Alla VM. Impact of Gender on In-Hospital Mortality and 90-Day Readmissions in Patients Undergoing Transcatheter Edge-To-Edge Mitral Valve Repair: Analysis From the National Readmission Database. Catheter Cardiovasc Interv. 2021;98.

[25] Marafino BJ, Escobar GJ, Baiocchi MT, Liu VX, Plimier CC, et al. Evaluation of an Intervention Targeted With Predictive Analytics to Prevent Readmissions in an Integrated Health System: Observational Study. BMJ. 2021;374.

[26] Stachel A. Development of a Hospital Readmission Reduction Program for Patients Discharged to Skilled Nursing Facilities: An Application of Artificial Intelligence and Machine Learning Techniques. 2020.

[27] Farid F, Bello A, Ahamed F, Hossain F. The Roles of AI Technologies in Reducing Hospital Readmission for Chronic Diseases: A Comprehensive Analysis. 2023.

[28] Golas SB, Shibahara T, Agboola S, Otaki H, Sato J, et al. A Machine Learning Model to Predict the Risk of 30-Day Readmissions in Patients With Heart Failure: A Retrospective Analysis of Electronic Medical Records Data. BMC Med Inform Decis Mak. 2018;18:44.

[29] Vidhya B, Fallah M, Vallabhaneni R, M D, Sundaram SM. Prediction of Medical Care Costs Using Random Forest Regressor for Personalized Healthcare. In 2025 3rd International Conference on Data Science and Information System (ICDSIS). IEEE. 2025:1-6.

[30] Paul D. Predicting Hospital Readmission Using Machine Learning: Evidence From Bangladesh and the United States Healthcare Systems. ResearchGate. 2024.

[31] Baechle C, Huang CD, Agarwal A, Behara RS, Goo J. Latent Topic Ensemble Learning for Hospital Readmission Cost Optimization. Eur J Oper Res. 2020;281:517-531.

[32] Veernapu K. The Role of Artificial Intelligence in Healthcare Finance: Improving Financial Forecasts and Operational Effectiveness. Int J Multidiscip Res Growth Eval. 2021;2:873-876.

[33] Hon CP, Pereira M, Sushmita S, Teredesai A, De Cock M. Risk Stratification for Hospital Readmission of Heart Failure Patients: A Machine Learning Approach. In Proceedings of the 7th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics. 2016:491-492.

[34] Baechle C, Agarwal A. A Framework for the Estimation and Reduction of Hospital Readmission Penalties Using Predictive Analytics. J Big Data. 2017;4:37.

[35] Salmons HI, Lu Y, Reed RR, Forsythe B, Sebastian AS. Implementation of Machine Learning to Predict Cost of Care Associated With Ambulatory Single-Level Lumbar Decompression. World Neurosurg. 2022;167.

[36] Mazza K. Conversational Artificial Intelligence and Patient Generated Health Data: Transitional Patient Applications to Improve Outcomes in the 30 Day Post-Discharge Window. Rutgers the State University of New Jersey, Rutgers School of Health Professions. 2020.

[37] Lopez CD, Boddapati V, Lombardi JM, Lee NJ, Mathew J, et al. Artificial Learning and Machine Learning Applications in Spine Surgery: A Systematic Review. Glob Spine J. 2022;12:1561-1572.

[38] Schulman AR, Dolan R, Abougergi MS, Telem D, Cohen-Mekelburg S. Impact of Fragmentation on Rehospitalization After Bariatric Surgery. Surg Endosc. 2021;35:291-297.

[39] Jain D, Durand W, Burch S, Daniels A, Berven S. Machine Learning for Predictive Modeling of 90-Day Readmission, Major Medical Complication, and Discharge to a Facility in Patients Undergoing Long Segment Posterior Lumbar Spine Fusion. Spine. 2020;45:1151-1160.

[40] Danda RR, Dileep V. Leveraging AI and Machine Learning for Enhanced Preventive Care and Chronic Disease Management in Health Insurance Plans. Front Health Inform. 2024;13.

[41] Potter R. Leveraging Predictive Analytics to Reduce Hospital Readmission Rates for Chronic Disease Patients. 2024.

[42] Sarijaloo F, Park J, Zhong X, Wokhlu A. Predicting 90 Day Acute Heart Failure Readmission and Death Using Machine Learning□Supported Decision Analysis. Clinical cardiology. 2021;44:230-237.

[43] BhanuPrakash C, S H. Predictive Analytics for Better Diabetic Patient Care: Insights From Xgboost, Random Forest, and Logistic Regression. In 2025 IEEE International Conference on Compute, Control, Network Photonics (ICCCNP). IEEE. 2025:1-6.

[44] Fares MY, Liu HH, da Silva Etges AP, Zhang B, Warner JJ, et al. Utility of Machine Learning, Natural Language Processing, and Artificial Intelligence in Predicting Hospital Readmissions After Orthopaedic Surgery: A Systematic Review and Meta-Analysis. Jbjs Rev. 2024;12.

[45] Lo YT, Liao JC, Chen MH, Chang CM, Li CT. Predictive Modeling for 14-Day Unplanned Hospital Readmission Risk by Using Machine Learning Algorithms. BMC Med Inform Decis Mak. 2021;21:288.

[46] Kalagara S, Eltorai AE, Durand WM, DePasse JM, Daniels AH. Machine Learning Modeling for Predicting Hospital Readmission Following Lumbar Laminectomy. J Neurosurg Spine. 2018;30:344-352.

[47] Zami A, Islam R, Zihan TM, Ahmed M. Risk Minimization by Early Readmission Prediction for Diabetes Patients: A Data-Driven Machine Learning Approach. In 2024 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON). IEEE. 2024:18-22.

[48] Mishra V, Tanniru MR, Sreedharan J. Prediction of 30-Day Readmission in Diabetes Management Using Machine Learning. Comput Biol Med. 2025;195:110616.

[49] Emi-Johnson OG, Nkrumah KJ. Predicting 30-Day Hospital Readmission in Patients With Diabetes Using Machine Learning on Electronic Health Record Data. Cureus. 2025;17.

[50] Lopez CD, Gazgalis A, Peterson JR, Confino JE, Levine WN, et al. Machine Learning Can Accurately Predict Overnight Stay, Readmission, and 30-Day Complications Following Anterior Cruciate Ligament Reconstruction. Arthroscopy. 2023;39:777-786.e5.

[51] Hassan A. Predictive Analytics and Decision Support for Heart Failure Patients. 2016.

[52] Échevin D, Li Q, Morin MA. Hospital Readmission Is Highly Predictable From Deep Learning. Chaire de Recherche Industrielle Alliance Sur Les Enjeux éConomiques Des. Chaire de recherche Industrielle Alliance sur les enjeux économiques des changements démographiques. 2017.

[53] Mazumdar M, Lin JJ, Zhang W, Li L, Liu M, et al. Comparison of Statistical and Machine Learning Models for Healthcare Cost Data: A Simulation Study Motivated by Oncology Care Model (OCM) Data. BMC Health Serv Res. 2020;20:350.

[54] Seyam EA. Predicting High-Cost Healthcare Utilization Using Machine Learning: A Multi-Service Risk Stratification Analysis in Eu-Based Private Group Health Insurance. Risks. 2025;13:133.

[55] Huang Y, Talwar A, Lin Y, Aparasu RR. Machine Learning Methods to Predict 30-Day Hospital Readmission Outcome Among Us Adults With Pneumonia: Analysis of the National Readmission Database. BMC Med Inform Decis Mak. 2022;22:288.

[56] Oluwagbade E, Animasahun B, Bakare A, Anthony OC. Leveraging Machine Learning to Predict Medication Adherence and Cardiovascular Outcomes Under Centralized Pharmaceutical Procurement: A Medicare Part D Analysis. Int J Adv Res Publ Rev. 2025;2:78-101.

[57] Uppuluri V. The Future of Business Intelligence in Value-Based Care Models. J Artif Intell Mach Learn Data Sci. 2018;1:3009-3015.

[58] Akinbode AK, Ifeanyichukwu Olinmah FI, Chima OK, Okare BP, Aduloju TD. Predictive Modelling for Hospital Readmission Using Socioeconomic and Clinical Data. Eng Technol J. 2025;10:6438-6465.

[59] Abreu J, Seringa J, Magalhaes T. Machine Learning Methods, Applications and Economic Analysis to Predict Heart Failure Hospitalisation Risk: A Scoping Review. BMJ Open. 2025;15.

[60] Raj S. Developing AI Models for Predicting Hospital Readmission Rates. Int Res Eng Manag. 2025;3.

[61] Alam MS, Rai P, Tiwari RK, Kumar B, Hussain S. Forecasting Hospital Readmission Rates in the US Using Time-Series Analysis and Machine Learning. In AIP Conference Proceedings 2026. 2026;3398:020002.

[62] Nambiar Jyothi R, Prakash G. A Deep Learning-Based Stacked Generalization Method to Design Smart Healthcare Solution. In emerging Research in Electronics, Computer Science and Technology, Proceedings of International Conference, ICERECT 2018. Berlin: Springer. 2019:211-222.

[63] Jones DG, Ratra A, Anstee C, Yasufuku K, Malthaner R, et al. Estimating Hospital Costs of Postoperative Adverse Events Following Esophagectomy: A Retrospective Cohort Study Involving 10 High Volume Canadian Hospitals. Curr Chall Thorac Surg. 2025;7:32.

[64] Chen H, Zeng Y, Cai D. Deep Learning for Cardiovascular Management: Optimizing Pathways and Cost Control Under Diagnosis-Related Group Models. Front Artif Intell. 2025;8:1580445.

[65] Salehi SS, Saadatfar H, Oyelere SS, Hussain S, Hassannataj Joloudari J, et al. Enhancing Healthcare Outcome With Scalable Processing and Predictive Analytics via Cloud Healthcare API. Front Digit Health. 2025;7:1687131.

[66] Zhao P. A Study of Unplanned 30-Day Hospital Readmissions in the United States: Early Prediction and Potentially Modifiable Risk Factor Identification. 2020.

[67] Huang Y, Talwar A, Chatterjee S, Aparasu RR. PNS143 Application of Machine Learning in Predicting Hospital Readmission: A Systematic Review of Literature. Value Health. 2020;23.

[68] Wu CX, Suresh E, Phng FW, Tai KP, Pakdeethai J, et al. Effect of a Real-Time Risk Score on 30-Day Readmission Reduction in Singapore. Appl Clin Inform. 2021;12:372-382.

[69] Aremu K, Olagunju Omotola Peggy. Advanced Machine Learning-Driven Business Analytics for Real-Time Health Risk Stratification and Cost Prediction Models. World J Adv Res Rev. 2025;26:150-167.

[70] Trento A, Rapisarda S, Bresolin N, Valenti A, Giordan E. Artificial Intelligence and Its Impact on the Management of Lumbar Degenerative Pathology: A Narrative Review. Medicina. 2025;61:1400.

[71] Shamim MM, Hamid AB, Nyamasvisva TE, Rafi NS. Advancement of Artificial Intelligence in Cost Estimation for Project Management Success: A Systematic Review of Machine Learning, Deep Learning, Regression, and Hybrid Models. Modelling. 2025;6:35.

[72] Soni A, Shivhare R. Predicting Disease Outcomes and Patient Readmission Rates Based on Her Using Machine Learning. Int J Res Manag Sci Technol. 2025;13:13101-13115.

[73] Mattie H, Reidy P, Bachtiger P, Lindemer E, Nikolaev N, et al. A Framework for Predicting Impactability of Digital Care Management Using Machine Learning Methods. Popul Health Manag. 2020;23:319-325.

[74] Mann A, Cleveland B, Bumblauskas D, Kaparthi S. Reducing Hospital Readmission Risk Using Predictive Analytics. INFORMS J Appl Anal. 2024;54:380-388.