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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 were searched, e.g., PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar.

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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 [1–3].

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 [4–7]. 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 populations 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.

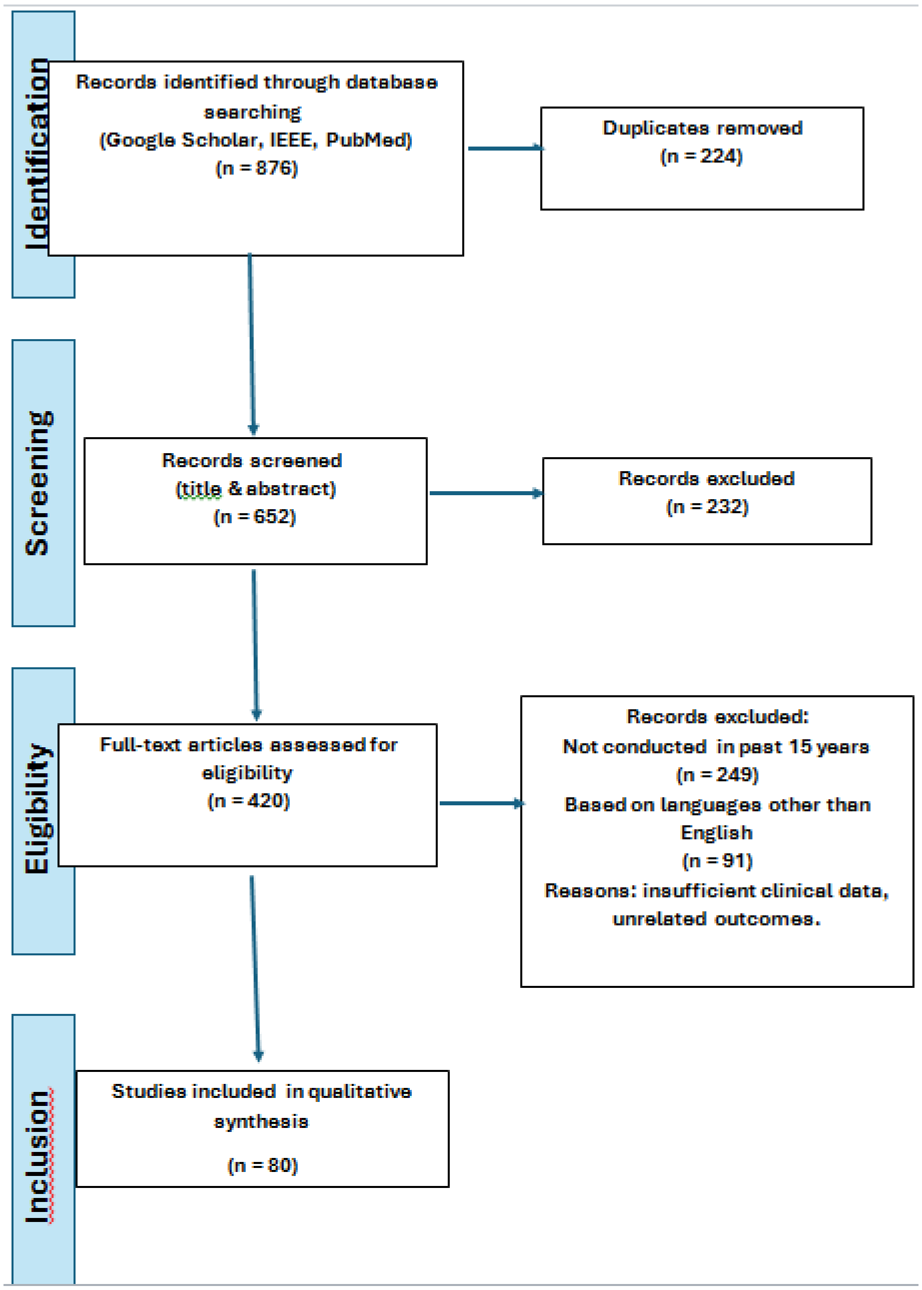
The qualitative analysis included a total of 80 studies. PRISMA allows a visual representation of the selection process, and shows the inclusion of studies for each of the steps (i.e., identification, screening, assessing eligibility, and inclusion), along with notes pertaining to the number of records 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 [14–17].

Random forest and other gradient boosting models, including XGBoost, were the ML algorithms that reported the best performance among the studies under review [18–20]. 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 [6, 21, 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 [24–26]. 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 [29–31]. In a system of reimbursement and penalties, the financial effects of readmission cases make this evidence particularly salient [32–34].

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 [35–37].

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. [22, 42].

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, 46–48]. Additionally, the research of hospital readmissions for diabetes has developed, and has been particularly emphasized in the management of chronic conditions. [49–51].

Research regarding the orthopedic and spine surgery patient populations has been successful as a result of defined postoperative pathways and expected recovery progress. [2, 40, 47, 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. [15, 53, 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. [39, 55].

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 [23, 57].

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 [7, 29, 31]. 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 [6, 21].

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, 35, 68].

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 [41, 72].

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, 19, 29, 43, 58, 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

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