Global Academic Journal of Medical Sciences

Available online at www.gajrc.com
DOI: https://doi.org/10.36348/gajms.2026.v08i01.003

OPEN ACCESS

ISSN: 2706-9036 (P)
ISSN: 2707-2533 (O)

Original Research Article

AI Models for Predicting Hospital Readmission Rates in Saudi Hospitals: Reducing Readmissions and Improving Quality of Care

Vijay Viswanathan[1]*

[1]Senior Consultant, IQVIA Solutions RHQ, Saudi Arabia

***Corresponding Author**
Vijay Viswanathan
Senior Consultant, IQVIA Solutions RHQ, Saudi Arabia

Article History
Received: 22.01.2026
Accepted: 17.03.2026
Published: 24.03.2026

Abstract: The readmission of patients into hospitals has been considered a measure of the quality of care delivered, the quality of discharge planning, and continuity of care. In Saudi Arabia, different digital health initiatives and advancements in electronic health record systems offer a timely opportunity to synthesize evidence on different artificial intelligence-based models for predicting hospital readmission risk and identify key design features of the model that are clinically relevant and useful. In this article, we have synthesized evidence on different artificial intelligence-based models for predicting hospital readmission risk and healthcare utilization outcomes using different machine learning and deep learning techniques and different explainable artificial intelligence techniques for predicting short-term hospital readmission risk and healthcare utilization outcomes within a 7-30-day window using peer-reviewed articles published between 2020 and 2025. The evidence on different artificial intelligence-based models for predicting hospital readmission risk and healthcare utilization outcomes using different machine learning and deep learning techniques and different explainable artificial intelligence techniques is discussed in detail with special emphasis on its applicability to hospital systems in Saudi Arabia. The gradient boosting and tree-based ensemble techniques are found to be consistently performing well for structured electronic health record-based predictive models. The representation learning-based techniques are found to be performing well for structured electronic health record-based predictive models. The outcome definition heterogeneity, class imbalance, temporal leakage, and lack of external validation are some of the limitations identified in different studies on artificial intelligence-based models for predicting hospital readmission risk and healthcare utilization outcomes. For hospital systems in Saudi Arabia, different factors need to be considered for developing artificial intelligence-based models for predicting hospital readmission risk and healthcare utilization outcomes. The methodological blueprint for hospital systems in Saudi Arabia is proposed using different artificial intelligence-based models for predicting hospital readmission risk and healthcare utilization outcomes based on different machine learning and deep learning techniques and different explainable artificial intelligence techniques using the PRISMA 2020 protocol and TRIPOD+AI protocol for systematic reviews and reporting of prediction model performance.

Keywords: Hospital Readmission, Saudi Arabia, Machine Learning, Deep Learning, Explainable AI, Electronic Health Records, Risk Stratification, Quality of Care.

Citation: Vijay Viswanathan (2026). AI Models for Predicting Hospital Readmission Rates in Saudi Hospitals: Reducing Readmissions and Improving Quality of Care. *Glob Acad J Med Sci*; Vol-8, Iss-1 pp- 24-34.

INTRODUCTION

The issue of unplanned readmission to health care facilities following a patient's discharge has been a major challenge to health care systems and society in general. This issue has been at the heart of many health care quality improvement endeavors. Many researchers have resorted to the use of predictive models to identify patients who are likely to experience readmission. This has been aimedat optimizing the use of transitional care resources. Saudi Arabia has been undergoing a paradigm shift towards the adoption of digital technologies. This has been aimed at achieving the objectives set in the vision 2030 report. This has been demonstrated by the adoption of electronic health care records. There has been an increased adoption of interoperability to facilitate the exchange of health care information between health care providers and the financial sector. This has been aimed at facilitating the sharing of health care and financial information without the need for tight coupling. This has been demonstrated by the ability to share information for the secondary use of routine clinical data. At the same time, the knowledge base on Al-based readmission prediction has been improving globally. This has been demonstrated by the improvement in model interpretability and representation learning. The process of predicting readmission has been faced with many challenges. This has been demonstrated by the need to consider many aspects beyond the accuracy of the model. This has been demonstrated by the need to consider the definition of the prediction problem and the process of building the model. This has been demonstrated in the case of Saudi Arabia. This has been demonstrated by the need to consider the process of coding and documentation. This has been demonstrated by the benefits of a national digital backbone and central governance. This paper follows the pattern of a systematic literature review on the use of AI for the prediction of the risk of readmission to the hospital, with particular emphasis on how the findings can be applied to the Saudi context. It also follows the pattern of literature on the topic of "Explainable Models for Readmission Prediction" as a basis for discussing how the prediction task can be approached and the benefits that can be derived from the use of such models for readmission prediction.

2. Aim and Objectives of the Study

Aim: The aim of the paper is to conduct a literature review on the use of Al for the prediction of the risk of readmission to the hospital, with particular emphasis on how the findings can be applied to the Saudi context.

Objective

1. To summarize the literature on the use of AI for the prediction of the risk of readmission to the hospital.
2. To provide a comparative analysis of the main algorithms that can be used for the prediction of the risk of readmission
3. To highlight some of the methodological pitfalls that can be encountered when using AIfor the prediction of the risk of readmission to the hospital.
4. To assess the quality of the reporting of the use of Al for the prediction of the risk of readmission to the hospital.
5. To provide a template for the use of the a template for the use of the prediction task, with particular emphasis on the context of the Kingdom of Saudi Arabia

3. REVIEW METHODOLOGY

3.1Design and Reporting Standards

For the research study, the methodology of "narrative systematic review" has been adopted. For the preparation of the report of this research study, the standards have been set based on "PRISMA 2020." While conducting the research the authors have followed the "TRIPOD-AI" checklist while evaluating the articles proposing prediction models using "machine learning" and "deep learning" algorithms.

3.2 Search Strategy

For the identification of articles, the authors have adopted "electronic database search" for "PubMed MEDLINE," "Scopus." "IEEE Xplore," and "Web of Science." For conducting this research study, the authors have selected articles from January 2020 to December 2025. While conducting the research, the authors have used "search terms" like "readmission." "rehospitalization," "30 days," "unplanned," "machine learning." "deep-learning," "gradient boosting." "XGBoost. "transformer." "embedding." "explainable," "SHAP," "LIME," etc. While conducting the research, the authors have used "search terms" like "Saudi Arabia," "Gulf" "Middle East," "EHR," "claims, " etc., for the identification of articles in the Kingdom of Saudi Arabia Gulf, and the Middle East regions. While conducting the research, the authors have used the reference list of the articles identified for this systematic review.

3.3 Eligibility Criteria

For the identification of the articles, the eligibility criteria selected by the authors are (a) definition of journal conference papers, (b) prediction model articles for readmission and other related outcomes, especially for readmission and other related outcomes within 90 days, especially 7-

30 days, (c) adult cohorts and disease-specific cohorts, (d) prediction models using routine clinical data, and (e) articles published from 2020 to 2025. The exclusion criteria selected by the authors are (a) pediatric cohorts, (b) articles without prediction models, (c) articles without sufficient methodological details, and (d) articles without English full texts, which cannot be translated.

3.4 Synthesis Approach and Quality Considerations

Due to the diversity of the data, results, and evaluation parameters, it is very important that we synthesize the results qualitatively. We have analyzed and compared the selected model based on AUC values. Best practices for predictive modeling include, but are not limited to, temporal splitting validation. Best practices for risk of bias in prediction models should be assessed using appropriate tools, as recommended in the latest literature.

4. Context: Readmission as a Quality and Operations Metric in Saudi Hospitals

There is also diversity in terms of the size and dynamics of hospitals in Saudi Arabia, as some of them are larger and academic, while others are smaller. The diversity of hospitals in Saudi Arabia could have an effect on the rate of readmission, especially with regard to patients who are outpatients. The severity of the disease and socio-factors could also have an effect on the rate of readmission. It is also possible to improve the prediction model by improving interoperability between healthcare facilities. There are guidelines that have been established with regard to the development of interoperable digital infrastructures for healthcare, including the exchange of data and health messages in different nations such as Saudi Arabia. Some studies have also been carried out with regard to the difficulties and opportunities with the development and use of EMRs, including the improvement of the quality of healthcare services and the development of prediction models such as the readmission prediction model. It is also argued that the model would not be effective in another hospital because of factors such as coding, orders, and procedures, among others. There are new prediction models that have been developed in Saudi Arabia, including machine learning classifiers for cardiovascular readmission prediction.

5. Data Sources and Problem Formulation

5.1 Structured EHR and Administrative Data

The majority of the existing models utilize structured data, which includes demographic data, diagnosis, comorbid conditions, vital signs, lab results, medication, length of stay, prior utilization, and discharge status. The addition of administrative data would enable the model to access longitudinal data from various facilities. Considering the strengthening relationship between payers and providers in the Saudi healthcare system, it would be beneficial to incorporate both the EHR and the administrative data to prevent the possibility of missing readmissions, which could potentially take place at facilities different from the one where the patient was discharged.

5.2 Clinical Text and Representation Learning

If the model includes the discharge and progress clinical text, the features based on natural language processing would be beneficial for obtaining more information regarding the patient's concerns, social factors, and physician uncertainty. The EHR embedding technique has been utilized for the prediction of heart failure readmissions, as per the recent studies [12]. The representation learning technique would be beneficial for reducing the dimensions of the patient history while maintaining the time pattern. The recent architectures, such as the use of the transformer, would be beneficial for integrating both the structured and unstructured data. However, the recent architectures have to be validated.

5.3 Outcome Definitions and Label Noise

Another problem with the existing studies is the different definitions of readmissions. Some models include only inpatient readmissions, while others include emergency department visits. It would have a major impact on the model performance. Another model for predicting readmissions for transplantation cases defined the following: "Our operational definition of readmission was broad, including all hospital encounters, which contributed to the high observed readmission rate. Our results are consistent with previous studies, but the definition of readmission used in this study was broader than in previous research." [7]. It is vital, especially for the Saudi healthcare system, to standardize the definition of readmissions while developing models. The model for the nurse phone call would have a different definition than the model for the beds.

6. Modeling Approaches

6.1 Strong Baselines: Regularized Regression and Tree-Based Ensembles

Logistic regression with regularization is perhaps the most commonly used model, and the simplicity of the model and ease of deployment have made this model very popular. However, in recent times, tree-based ensemble models have been at the forefront in developing a strong baseline model. For example, a recent model was proposed for the task of 30-Day Readmission after Renal Transplantation using gradient boosting as a model for feature interpretation. SHAP values and LIME values are used in the model to validate the model. Although this model was proposed for a different population than the general healthcare system in Saudi Arabia, the model is based on a model that can be used on different populations in different hospitals in the country. The model includes a strong ensemble model, a leakage prevention model, and an explanation model to validate the model.

6.2 Deep Learning for Longitudinal EHR

Deep learning models have shown promise in exploiting the longitudinal data in the EHR data to develop predictive models. For example, in a recent study, it was indicated that DL-based models perform better than traditional models in the task of predicting unplanned 30-Day Readmission for patients with diabetes. It was indicated that the performance improvement of the DL-based models can be attributed to the availability of previous encounters in the patient's records. However, in order to make use of the performance improvement of the DL-based models in the context of EHR in Saudi Arabia, there should be a system to govern the longitudinal records.

6.3 Embeddings and Transformers

Studies have been carried out to evaluate the performance of learned embedding representations of EHR codes and notes for readmission prediction tasks. Comparative studies have also been carried out to evaluate learned embedding representations of EHR codes and notes for heart failure readmission prediction tasks. In another study, transformer-based clinical language models are utilized for readmission prediction tasks using clinical notes. The results of this study revealed that performance benefits are available with the use of clinical notes. This study has a high potential for application in the Saudi context because bilingual notes are used in healthcare settings.

6.4 Explainable AI (XAI) to Support Adoption

One of the key factors for the adoption of predictive models is interpretability for hospital readmission prediction tasks. Clinicians should be convinced to adopt the proposed intervention for hospital readmission prediction tasks. SHAP values and LIME are still the most widely used techniques for global and local interpretation of AI models. In recent reviews on XAI in the medical domain, it is highlighted that results lead to increased or reduced trust in AI systems. In another study on XAI in healthcare, it is highlighted that performance benefits are available in predicting modifiable risk factors for hospital readmission prediction tasks. In another study on XAI in healthcare, it is highlighted that high feature importance does not necessarily imply intervention benefits.

6.5 Feature Engineering Patterns

Feature engineering in research conducted between 2020 and 2025 can be divided into four major groups. These groups are as follows:

The first group of features is the basic features of the patients. This includes the ages of the patients, the sex of the patients, the nationality of the patients, the class of insurance, and geographical features.

The second group of features is the clinical burden. This includes comorbidity indices, problem lists, and diagnosis grouping.

The third group of features is the severity and trajectory of illness. This includes early warning scores, the volatility of the vital signs, lab trends, and the need for intensive care.

The fourth group is the utilization and process of care. This includes previous admissions, emergency visits, the length of stay, and discharge destinations, as well as follow-ups for those who are outpatients.

One of the interesting things to note from all the studies that were done within this period is that the utilization history was very predictive. For disease-specific populations, there exist certain lab and treatment markers that are prominent within different populations. For the transplantation population, length of stay and systolic blood pressure were the major predictors. For the rest of the populations, BMI and glycemic control varied depending on the different subgroups of the donors. It seems that the major predictors for different populations may not be the same. For the general medicine population, the features that are common predictors of early return include the complexity of the medication, the risk of polypharmacy, unstable renal function, and so forth. For the Saudi hospitals, the reliability of the features can be enhanced by standardizing the lab units and ranges. Additionally, it would be beneficial to set a standard time window for the features. For instance, the features can be set for the last 48 hours prior to the discharge date. For the multi-facility systems, the features for the fragmentation of the care can be enhanced. For instance, the features can be set for the transfer from one facility to another or for delayed visits to the out-patient department.

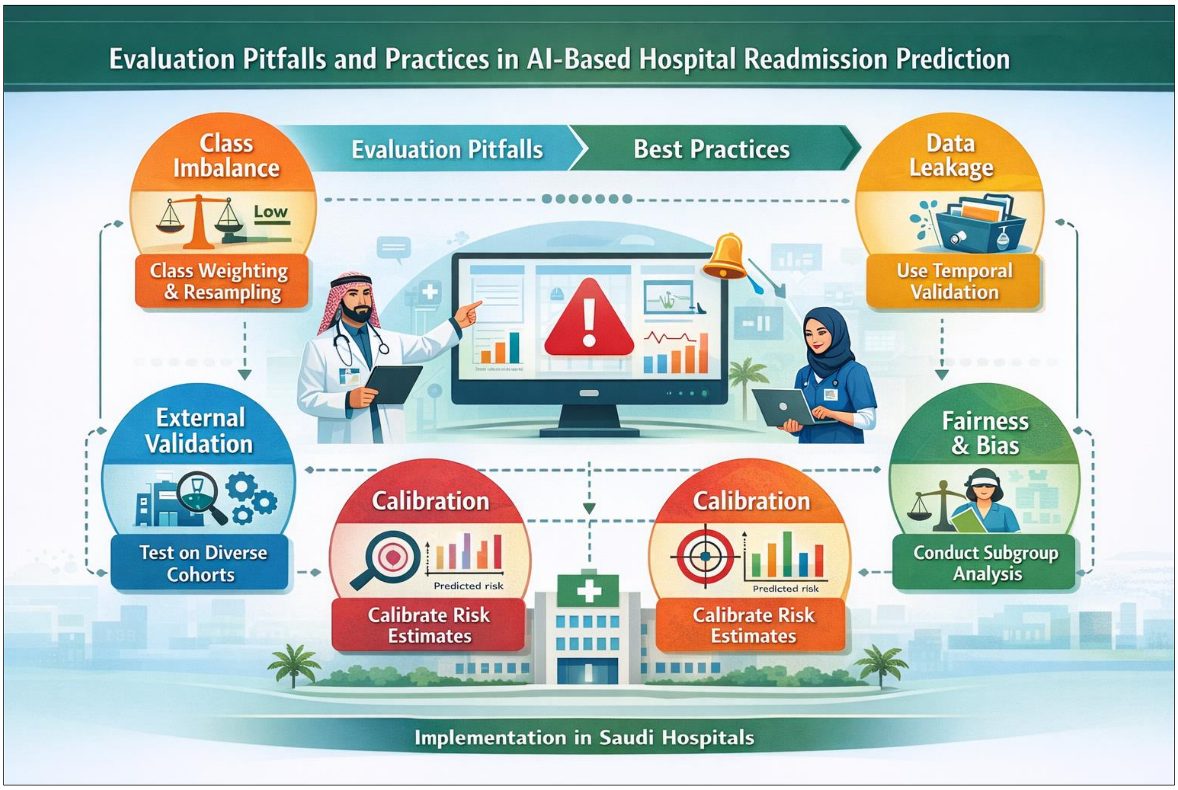
6.6 Handling Missingness and Data Quality

It is natural for EHRs to have missing values. Not all labs have been ordered for all patients. Additionally, not all variables have been collected for all departments. The range of techniques used for handling missing values can be simple to very complex. Tree-based models have the capability to handle missing values internally. Additionally, linear models require handling missing values. Deep models require handling missing values. For the deployment of the model, the missing values mechanism can be considered as an important feature. Not all tests have been ordered for all patients. Additionally, not all patients have ordered many tests. The missing values can be considered as indicative of the clinical conditions. Additionally, the missing values can be considered as indicative of the severity of the disease. For this reason, the top-performing models have considered the missing values as well as the imputed values. For the Saudi hospitals, the missing values should be documented for each unit as well as for each department. The changes in the pattern of lab orders over time can be considered as a clinical shift. In the case of models that incorporate the clinical text as well, documentation is a major issue that needs to be taken care of. In the case of the hospitals that use both the Arabic and English languages, there can be a negative impact on the NLP features unless the process of tokenization and normalization has specifically been carried out for the hospitals.

Table 1: Representative 2020–2025 studies and review evidence informing Saudi hospital readmission prediction

Study	Setting / Cohort	Outcome horizon	Data modalities	Model family	Best reported performance	Explainability	Key notes for Saudi applicability
Alzeer *et al.*, (2021)	Saudi Arabia; cardiovascular	30-day readmission	Structured EHR	ML classifiers	Reported as competitive vs baselines	Limited	Single-site; highlights local feasibility
Hai *et al.*, (2023)	US; diabetes	30-day unplanned	Common Data Model EHR	LSTM vs RF/LR	AUROC ~0.79 (LSTM)	Limited	Longitudinal encounters improve DL
Jahangiri *et al.*, (2024)	Nationwide dataset; HF	30-day	Administrative + clinical	XGBoost/ML	AUC reported; feature set optimization	Some	Emphasizes feature selection
Shakya *et al.*, (2025)	MIMIC-IV; HF	30-day	Codes + embeddings	XGBoost/LR/ANN	AUROC improved (e.g., 0.65 vs 0.54)	Some	Embeddings add value; external validation needed
Pandey *et al.*, (2025)	Multimodal; notes + structured	30-day	Structured + text	ClinicalT5 hybrid	Improved discrimination vs single-modality	Limited	Text integration requires strong governance
Alnazari *et al.,* (2025)	Saudi Arabia; renal transplant	30-day	EHR + labs + vitals	Gradient boosting	AUC 0.837	SHAP + LIME	Web deployment; stresses external validation
Alnomasy *et al.*, (2025)	Systematic review; HF	Varies	Varies	ML/DL	Mixed; heterogeneity high	Varies	Recommends PRISMA-aligned synthesis
Alkhanbouli *et al.,* (2025)	Systematic review; XAI	N/A	N/A	XAI methods	N/A	SHAP/LIME focus	Notes gaps in dataset diversity and robustness

7. Evaluation Practices and Common Pitfalls



7.1 Discrimination, Calibration, and Clinical Utility

The vast majority of papers will have some form of discrimination metrics, such as AUC, F1 score, and precision/recall metrics. Calibration is less frequently reported. Calibration is of particular interest for resource allocation using risk thresholding approaches. It is strongly recommended that model development, validation, and performance be included. Calibration should also be included with associated uncertainties. Calibration is going to be of significant interest in the Saudi implementation because of the very different readmission rates. Decision-analytic performance metrics such as net benefit and workload-adjusted precision at top k percentiles could be of interest in linking model outputs to decision-making processes. Note that it is also worth mentioning that it is possible for a model to have poor discrimination (e.g., low AUC) but still be very useful for a hospital that is able to intervene on the top decile of risk patients based on capacity and resource constraints.

7.2 Class Imbalance and Rare Outcome

The rates of readmission, as defined here, are low. This is known as class imbalance and is known to cause unstable positive predictive values. There are several approaches to handle class imbalance, including class weighting, resampling approaches, and focal loss for DL and threshold calibration. Note that resampling is known to cause unstable probabilities.

Note that it is worth mentioning that for the Saudi implementation, it is not F1 optimization that is of interest but rather probability-calibrated risk estimates.

7.3 Data Leakage and Temporal Validation

Data leakage occurs when we are using features that will be available after discharge and not before discharge, when we are making a prediction. This will be a problem because it will cause optimistic performance that will not generalize well. For the implementation in Saudi Arabia, it will be important to know whether we are making a prediction 24 hours before discharge or at discharge. It will also be important to perform temporal validation for this problem. We have learned that many papers still use random validation sets.

7.4 External Validation and Transportability

It will be important to perform external validation on the model that we have developed. This is because we have learned that it will be a problem when we generalize. The transplant XAI model has also shown us the importance of performing external validation before we use it. For the implementation in Saudi Arabia, it will be important because there will be a difference in hospital referral for outpatients.

7.5 Fairness, Equity, and Bias in Readmission Prediction

There will be a potential for exacerbating health inequities in the model that we have used for readmission prediction. There will be barriers and differences that will be used as risk factors in the model that we have used for readmission prediction. For example, patients that are farther from a tertiary hospital will have barriers in accessing outpatient visits. In addition, socioeconomic status will be a risk factor for readmission. These patients already have barriers in access to healthcare and will have a high risk of readmission and are not being properly addressed in the model that we have used for prediction. There will also be an exacerbation of health inequities. There is no recommendation for a fairness evaluation. For the model we have used for readmission prediction in the Kingdom of Saudi Arabia, there would be new recommendations for a fairness evaluation. For example, subgroup evaluation would be recommended. There is a potential for explainability to identify biases that have been embedded in the model, for example, the presence of sensitive attributes such as nationality, zip code, and hospital sites. Explainability could lead to false positives, especially where there are attributes and sites. Fairness evaluation is not only a model evaluation criterion but also a process criterion.

7.6 Linking Prediction to Action: Intervention-Aware Evaluation

To make use of the readmission model, it is essential to think about what is possible based on what is being predicted. There is a very high possibility that most of these models were developed and implemented without considering "intervention-aware evaluation." Thus, it is important for Saudi hospitals to think about what is being done after a patient is identified as being at risk and evaluate them. For example:

- For high-risk patients: medication reconciliation, patient education, and scheduling of a follow-up appointment within 72 hours.
- For moderate risk patients: post-discharge call within 48 hours and scheduling of appointment.
- For low-risk patients: standard care, patient education, and instructions via patient portals.

This is much more realistic since this is much more likely to happen since the selection of models is based on what is possible. There are even cases when a model, even though not as accurate, is much more interpretable and has much more stable risk tiers and might even perform much better than a "black box" model.

8. Implementation and Governance in Saudi Hospitals

8.1 Interoperability and Data Standardization

This is useful in capturing the readmissions from different hospitals than the index hospital. This will be very helpful in improving the overall features. It is also useful because the national exchange guidelines have a structure for clinical and financial exchange [5]. This is very useful in model building because the historical data can be used to make improvements to the overall performance of the model. It is also useful because ICD coding, procedures, medications, and lab values need to be standardized. "Document differences between hospital groups can lead to spurious effects on features."

8.2 Workflow Integration and Human Factors

There is a possibility that successful models can fail if they are not integrable. There are barriers to the adoption of EMRs in Saudi. The barriers include change, usability, and training. It is essential to integrate the readmission model with the discharge planning workflow with minimal cognitive burden, risk tiers, explanations, and actions.

8.3 Explainability Interfaces and Accountability

It is essential that the XAI be tailored to the user based on their needs. It is possible that the discharge nurses may need fewer than ten actionable drivers. On the other hand, the physicians may need more. A pattern was followed for global and local explanation frameworks, SHAP and LIME, respectively. The model will be used in the prediction of readmission for patients admitted in Saudi Arabia [7].

8.4 Monitoring, Drift, and Updating

There is a possibility that the readmission drivers can change over time. The change can be influenced by different factors like care pathways, updates, and staffing. It is essential to monitor the calibration drift, fairness across subgroups like sex, age, region, and comorbid. Concept drift because of updates in coding. It is essential to update with version control. The updating should be done in silent mode.

8.5 Privacy, Security, and Secondary Use Governance

The reason for this is that the information shared is very sensitive and pertains to patients. When it comes to the Saudi model, it is specified that the process of information extraction, the extraction of information for research and de-identification, and access based on roles for clinical tools have been approved. Once the models have been implemented, there are various security concerns that have to be addressed, which include audit trails for prediction, retention of input and output for models, and response to incidents.If it becomes necessary for these models to be implemented in various hospitals, federated learning and data enclaves can be used, which would possibly minimize the movement of the data. It would also possibly make the models more complex and less debuggable. It would possibly be possible as the first step to standardize the pipelines at the local level, sharing model specifications and not data, and exploring multi-site validation and data sharing.

8.6 Model Maintenance: From 'One-Time Build' to 'Lifecycle Management

There is degradation in the quality of healthcare models over time, and there are several factors, including those related to healthcare, like changes in case mix, coding, and clinical practices, and those unrelated, like economic crises and natural disasters. As far as the proposed methodology for model deployment with the TRIPOD+AI framework is concerned, there is reporting of model performance, as well as additional documentation for model deployment support, model cards, thresholds rationale, monitoring dashboards, etc. As far as the proposed methodology is concerned, in relation to the Saudi healthcare environment, there is scope for the central government structures to be able to take care of monitoring models in different healthcare facilities, as well as having the flexibility to adapt thresholds based on the capacity of intervention in different healthcare facilities.

9. Proposed Saudi-Context Methodological Blueprint

As far as the proposed methodology for model deployment is concerned, we propose a blueprint for implementation in relation to different healthcare facilities in Saudi Arabia.

1) Definition of outcome of interest for improvement through intervention and definition of time point of interest for prediction (e.g., unplanned readmission within 30 days of discharge and discharge order signed).
2) Development of a data mart for all facilities with standard codes and units of measurement.
3) Development of baseline models using regularized regression and gradient boosting methods and documentation of preprocessing and handling of missing and leakage.
4) Model development and deployment of the TRIPOD+AI approach and its recalibration, as well as the estimation of uncertainty and predictors and handling of missing values [2].

5) Application of XAI techniques and templates that are validated by clinicians and evaluation of results consistency over time and at different locations…
6) Evaluation of clinical utility of the model using parameters such as ability to intervene, number of alerts, and improvement in outcome for pragmatic trials…
7) Establishing a framework of governance as per the digital health policies of the country, including privacy, auditing, and monitoring aspects…

The blueprint will be a framework for a stepwise approach for model adoption. This will involve using ensemble models for structured data and then using embeddings and NLP models as and when data quality and governance are advanced

9.1 Recommended Technical Methodology for Saudi Hospital Deployment

The blueprint is mapped to a recommended technical methodology for the deployment in Saudi hospitals as follows:

Step A: Data Definition and Extraction

- Define index admission and exclusion criteria such as transfers, death, and planned readmissions.
- Define readmission window.
- Ensure consistency of data identifier across hospitals.
- Define feature cutoff definition such as discharge - 6 hours prior to hospitalization…

Step B: Data Preprocessing and Quality

- Define missing data and latency issues.
- Normalize data.
- Encode categorical variables.
- Create time window summaries for vital signs and lab results, such as mean and last observation carried forward, and slope.

Step C: Develop Model

- We will create a logistic regression model with regularization, as well as a gradient boosting model, as our first model.
- We will use nested cross-validation for tuning our model. We will utilize a temporal validation set with the last time period held out.

Step D: Model Explainability

- We will utilize SHAP for model explainability.
- We will create templates for model explanations that will show the relationship between drivers and actions (e.g., 'Frequent ED visits -> Schedule follow-up appointments').
- We will have review sessions with clinicians to validate our model for plausibility.

Step E: External Validation

- We will validate our model in another hospital in Saudi Arabia with a different population.
- If our model changes in performance, we will recalculate the results.

Step F: Deployment

- We will integrate our model with the EHR system as well as the discharge system with tiered alerts.
- We will deploy the model in "silent" mode to validate for fatigue.

Step G: Outcome Evaluation

- We will conduct a pragmatic quality improvement study to compare our model with respect to readmission rates, patient satisfaction, and equity before and after deployment.
- We will adjust for seasonality effects.

10. Research Gaps and Future Directions

Although there is a rise in the volume of evidence, there are some gaps. For example, calibration information and the use of random splits are very important, especially in the development of these models. Another gap is the need for research to be carried out under the auspices of the Kingdom, such as developing and testing multi-center datasets and setting evaluation standards. Another gap is the need for research to be carried out concerning the potential impacts of evaluation, which is very important in the evaluation of these models, not only for readmission but also for other aspects concerning patients and unintended effects. The field is moving towards developing new tools for appraisals, which is fundamental in the evaluation of prediction models using AI techniques. This is very important in providing unbiased evaluation, such as risks of bias and appropriateness. This is very critical in hospitals in the Kingdom, especially in the procurement and governance phases, where there is a need to increase transparency from the contractors and researchers.

10.1 Practical Research Agenda for Saudi Arabia

Future research needs to focus on the following areas:

1) Developing multi-center datasets from Saudi Arabia with standardized outcome definitions;
2) Rigorous temporal and external validation;

3) Calibration and decision curve analysis;
4) Bilingual NLP resources for clinical documentation;
5) Prospective evaluation studies.

One area of research that could be considered for future research shall be the incorporation of national exchange data, which would enable the model to become more effective for the detection of readmissions, thus improving the label noise. This would enable the model to track the utilization of the patient appropriately [5].

One area of research that could be considered for future research, especially from the perspective of the country of Saudi Arabia, could be the development of "model registries" that would enable the integration of prediction tools, training, and validation studies.

11. CONCLUSION

Based on the above discussion, it is evident that there is significant progress in the area of AI prediction of readmissions from 2020 to 2025, and there is considerable evidence of the effectiveness of tree-based ensemble models with structured EHRs and emerging evidence of the potential benefits of embeddings and transformers with longitudinal and textual data. Although the prediction models have become more and more precise, it is essential that the model is "leakage-free, calibrated, externally validated, and integrated into practice with explanations that can be trusted." Considering the national digital transformation, improvement of exchange, and improvement of local analytics, it is evident that the prospects for improving the prediction of readmissions for the country of Saudi Arabia are excellent. Considering PRISMA 2020 and TRIPOD+AI, it is evident that the country of Saudi Arabia could move from modeling to effective interventions.

REFERENCES

1. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. doi:10.1136/bmj.n71.
2. Collins GS, Moons KGM, Dhiman P, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ. 2024;385:e078378. doi:10.1136/bmj-2023-078378.
3. Moons KGM, et al. PROBAST+AI: an updated quality, risk of bias, and applicability assessment tool for prediction models using regression or artificial intelligence methods. BMJ. 2025;388:e082505. doi:10.1136/bmj-2024-082505.
4. Alhur A, Alghamdi A, et al. Overcoming electronic medical records adoption challenges in Saudi Arabia: a literature review. Cureus. 2024;16:e53827. (PMCID: PMC10924290).
5. Council for Health Insurance (CHI), Saudi Arabia. NPHIES Healthcare Financial Services Implementation Guide—Introduction (accessed 2025).
6. Alzeer AH, et al. Using machine learning to reduce unnecessary hospital readmissions for cardiovascular patients. International Journal of Medical Informatics. 2021;154:104590. doi:10.1016/j.ijmedinf.2021.104590.
7. Alnazari N, Alanazi OI, Alosaimi MO, et al. Development of explainable artificial intelligence based machine learning model for predicting 30-day hospital readmission after renal transplantation. BMC Nephrology. 2025;26:203. doi:10.1186/s12882-025-04128-w.
8. Hai AA, Weiner MG, et al. Deep learning vs traditional models for predicting hospital readmission among patients with diabetes. AMIA Annual Symposium Proceedings. 2023;2022:512–521. PMID:37128461.
9. Zhao H, Tanner S, Golden SH, Fisher SG, Rubin DJ. Common sampling and modeling approaches to analyzing readmission risk that ignore clustering produce misleading results. BMC Medical Research Methodology. 2020;20:281. doi:10.1186/s12874-020-01162-0.
10. Jahangiri S, et al. A machine learning model to predict heart failure 30-day readmissions using a nationwide hospitalization database. Frontiers in Artificial Intelligence. 2024;7:1363226. doi:10.3389/frai.2024.1363226.
11. Alnomasy N, et al. Predictive performance of machine learning models for heart failure readmission: a systematic review. Biomedicines. 2025;13:2111. doi:10.3390/biomedicines13092111.
12. Shakya P, Khaneja A, Wagholikar KB. Predicting 30-days hospital readmission for patients with heart failure using electronic health record embeddings: comparative evaluation. JMIR Medical Informatics. 2025;13:e73020. doi:10.2196/73020.
13. Pandey SR, et al. Predicting 30-day hospital readmissions using ClinicalT5 with structured and unstructured data integration. PLOS ONE. 2025;20:e0328848. doi:10.1371/journal.pone.0328848.
14. Guo C, et al. Towards an explainable machine learning model to reduce readmission risks for diabetic patients. (Elsevier/Heliyon). 2025; (Article: S2352914825000759).

15. Al Moussawy M, et al. Transformative potential of artificial intelligence in solid organ transplantation. Frontiers in Transplantation. 2024;3:1361491. doi:10.3389/frtra.2024.1361491.
16. Fabreti-Oliveira RA, et al. Predicting kidney allograft survival with explainable machine learning. Transplant Immunology. 2024;85:102057. doi:10.1016/j.trim.2024.102057.
17. Ali H, et al. Artificial intelligence assisted risk prediction in organ transplantation: a UK live-donor kidney
18. Alkhanbouli R, et al. The role of explainable artificial intelligence in disease prediction: a systematic literature review and future research directions. 2025. (PMCID: PMC11877768).
19. Hassija V, Chamola V, Mahapatra A, et al. Interpreting black-box models: a review on explainable artificial intelligence. Cognitive Computation. 2024;16(1):45–74. doi:10.1007/s12559-023-10179-8.
20. Ratti E, Graves M. Explainable machine learning practices: opening another black box for reliable medical AI. AI and Ethics. 2022;2:801–814. doi:10.1007/s43681-022-00141-z.
21. Srinivasu PN, Sandhya N, Jhaveri R, Raut R. From blackbox to explainable AI in healthcare: existing tools and case studies. Mobile Information Systems. 2022;2022:8167821. doi:10.1155/2022/8167821.
22. Gotlieb N, Azhie A, Sharma D, et al. The promise of machine learning applications in solid organ transplantation. NPJ Digital Medicine. 2022;5:89. doi:10.1038/s41746-022-00637-2.
23. Balch JA, et al. Machine learning applications in solid organ transplantation: a review. 2021. (PMID:34603324).
24. Akl EA, et al. Extension of the PRISMA 2020 statement for living systematic reviews (PRISMA-LSR): checklist and explanation. BMJ. 2024;387:e079183. doi:10.1136/bmj-2024-079183.
25. Sharma Y, et al. Performance of machine learning models in predicting 30-day readmissions: retrospective evaluation in general medicine admissions. 2025. (PMCID: PMC12153988).
26. Kaul T, et al. Assessing the quality of prediction models in health care: using PROBAST and related tools. Journal of Clinical Epidemiology. 2025; (S0895-4356(25)00065-4).
27. Zhang Y, Weng Y, Lund J. Applications of explainable artificial intelligence in diagnosis and surgery. Diagnostics. 2022;12(2).
28. Peloso A, Naesens M, Thaunat O. The dawn of a new era in kidney transplantation: promises and limitations of artificial intelligence for precision diagnostics. Transplant International. 2023;36:12010. doi:10.3389/ti.2023.12010.
29. Gotlieb N, et al. (Supplementary) ML in transplantation and digital medicine perspectives for deployment and governance. NPJ Digital Medicine. 2022;5:89.