

AI-Driven Early Detection Models for Chronic Diseases in Saudi Arabia: A Systematic Review and Translational Framework

Vijay Viswanathan

IQVIA REGIONAL HEADQUARTERS, Saudi Arabia, ORCID ID: 0009-0002-3919-5047

Abstract

Background : In Saudi Arabia, chronic health issues like diabetes, heart disease, and cancer are on the rise. They lead to avoidable complications and result in higher healthcare expenses. By utilizing clinical data from EHRs and lab results, machine learning can play a significant role in the prevention of potential problems.

Objective : The present review aims to provide research articles from 2020-2025 on how artificial intelligence and machine learning can contribute to the early detection or prediction of risks of developing diabetes, heart disease, and cancer. In addition, it aims to provide a framework that can be applied in the present reporting and evaluation standards.

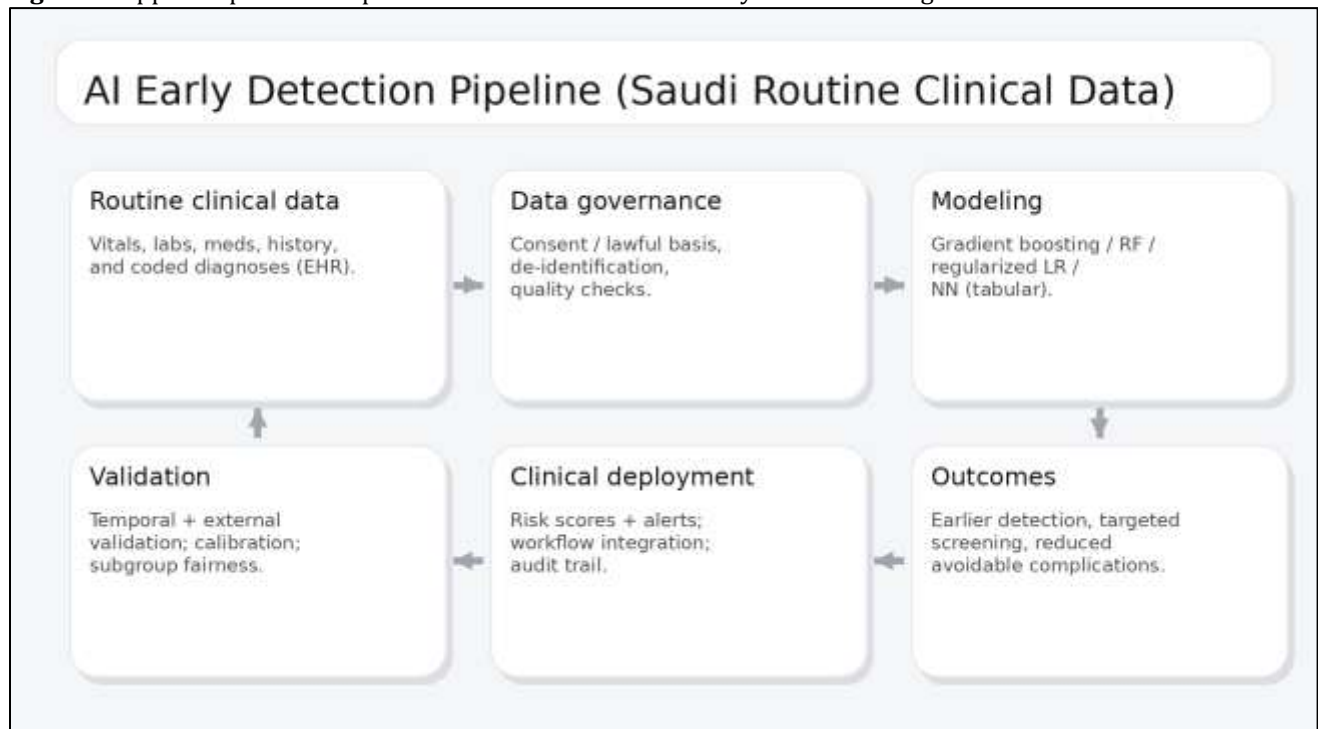
Methods : The present review was done based on the PRISMA 2020-2025 guidelines, including literature from MEDLINE/PubMed, Scopus, IEEE Xplore, and Google Scholar databases from January 2020 to December 2025.

Results : The evolution of research from small tables of data to bigger populations from EHRs, utilizing feature engineering, and decision tree algorithms was observed. In Saudi Arabia, diabetes research was initially based on modeling disease progression and age of onset, but it now includes modeling disease onset and progression. Cardiovascular disease research was based on stratification and helping in the early diagnosis of the disease.

Conclusion : The potential of artificial intelligence and machine learning in the early detection of diabetes, heart disease, and cancer can be promising. However, it would require better governance and evaluation.

Keywords: Saudi Arabia; machine learning; early detection; diabetes; cardiovascular disease; cancer; electronic health records; risk prediction; explainable AI; clinical decision support

Figure 1. Apple-inspired conceptual workflow for AI-driven early detection using routine clinical data.



1. Introduction

A significant amount of avoidable illness and death has been caused by chronic diseases in the Gulf region. This is, in some part, a result of significant shifts in lifestyle, including urbanization, new dietary habits, and reduced physical activities. In Saudi Arabia, diabetes and heart diseases are the key causes of health concerns, whereas cancers such as breast and colon cancers are becoming more important for screening and early detection. Early detection of these diseases, identifying individuals with high risk factors or signs of disease before serious harm

is done, can be useful in achieving better outcomes by allowing individuals to make lifestyle modifications, undergo tests, and receive earlier treatment.

Routine clinical data, including patient demographics, vital signs, lab results, medication history, diagnosis, and visit history, is valuable for early detection of diseases since this data is generally collected during routine patient care. Machine learning can identify intricate data patterns beyond conventional risk factors. Nevertheless, for machine learning to be useful in a real-world setting, it must be generalizable, well-calibrated, fair, and seamless in integration with healthcare processes, all while being data governance-compliant.

The last few years have seen a rise in the number of reporting standards and guidelines for assessing AI, including PRISMA 2020 for systematic reviews [1], CONSORT-AI and SPIRIT-AI for trials of AI interventions in studies [2,3], TRIPOD-AI for reporting prediction models, and STARD-AI for studies of diagnostic performance with AI [5,6]. All of these guidelines emphasize the need for transparent data provenance, development, validation, error analysis, and human-AI interaction, all of which are of utmost importance in high-risk applications in healthcare settings. This paper follows an evidence synthesis approach in presenting research in machine learning and healthcare, divided into clear sections for readers to understand the evidence presented to arrive at a conclusion and make appropriate recommendations for implementation.

2. Aim and Objectives

2.1 Aim

To investigate and critically assess evidence from 2020 to 2025 for AI/ML models for the early diagnosis/risk prediction of diabetes, CVD, and cancer in Saudi Arabia from general clinical data, and to provide a way forward for its safe and effective implementation.

2.2 Objectives

- 1) To provide data, features, and algorithm variables for the early diagnosis of chronic diseases in Saudi Arabia.
- 2) To investigate assessment strategies for machine learning models, with a focus on external validation, calibration, and subgroup analysis.
- 3) To provide a description of the current status of clinical translation, including governance, interpretability, and future impact evaluation.
- 4) To provide a blueprint for stepwise implementation in the Saudi healthcare setting and digital transformation.

3. Methods

3.1 Review design

A systematic review was done based on the PRISMA 2020 guidelines [1]. Eman Alghareeb and Najla Aljehani, in their review, stated that “due to the differences in the results of the studies on AI in healthcare, the data used, and the evaluation tools, the review was based on a narrative review with structured data extraction.” The inclusion criteria of the review were that the articles were published between 2020 and 2025, used ML/AI on structured regular clinical data, predicted new cases of any of the following: diabetes, heart disease, cancer, (iii) machine learning or artificial intelligence, and (iv) routine clinical data like EHR, lab results, or claims. They were excluded based on the following reasons: if the articles were only on imaging models without the use of regular clinical data, did not include the Saudi population, or were not methodologically sound. We obtained the following information from each included study: cohort and setting (e.g., sample size, population, time frame of data collection), types of predictors (e.g., demographics, lab values, vital signs, diagnoses, medications, healthcare utilization), algorithms used (e.g., logistic regression, random forest, gradient boosting, neural networks), how outcome measures and prediction timeframes were defined, how missing data was handled, feature selection or engineering, how the model was validated (e.g., random split, temporal split, cross-site validation), metrics used to evaluate discrimination (e.g., AUC, accuracy, F1), metrics used to evaluate calibration (e.g., Brier score, calibration slope, calibration intercept), how the model was explained, and whether subgroup analysis was performed, including fairness analysis.

3.2 Search Strategy and Eligibility Criteria

The search strategy was based on four main concepts: (i) Saudi Arabia, (ii) chronic illnesses like diabetes, cardiovascular disease, and cancers, (iii) ML/AI, and (iv) routine clinical data like EHRs, lab results, and claims/encounter data. We considered the ensuing eligibility criteria: (a) year of publication between 2020 and 2025, (b) ML/AI was used to analyze RCD, (c) the study was aimed at predicting diseases, clinical events, or conditions that are amenable to early prediction, and (d) at least one quantitative metric was provided in the study. We did not include studies that: (a) did not use RCD, (b) did not have a cohort from Saudi Arabia, or (c) did not provide enough details of their methodology. A PRISMA flow diagram would be provided in Section 3.2 to ensure maximum transparency, showing all decision points.

3.3 Data Extraction

To guarantee that all necessary details are provided in the systematic review, the following data would be extracted from the studies: (a) details of the cohort like sample size, population, data collection period, (b) types of predictors like demographics, labs, vital signs, diagnoses, medications, utilization, (c) ML/AI algorithms including regularized logistic regression, random forests, gradient boosting machines, neural networks, etc., (d) outcome of interest and prediction horizon, (e) handling of missing data, (f) feature selection/engineering, (g) validation strategies like random split, temporal split, cross-site validation, (h) numerical measures like AUC, accuracy, F1-score, (i) calibration statistics like calibration plots, Brier score, calibration slope, calibration intercept, (j) explainability, and (k) fairness and subgroup analysis.

3.4 Quality and transparency appraisal

Instead of using a numerical rating system, we evaluate the quality of each study based on its level of detail in reporting itself against the criteria for diagnostic model studies proposed in the TRIPOD-AI framework. Additionally, we evaluate studies based on their level of detail in reporting human-AI interaction and monitoring, as suggested in the SPIRIT-AI/CONSORT-AI criteria for future studies.

3.5 Synthesis plan

We identified studies based on different types of diseases: diabetes, cardiovascular diseases, and cancer. We also identified studies based on different types of approaches used in developing AI systems: (i) studies that are more focused on model development, (ii) studies that involved some form of validation for their models, and (iii) studies that are more focused on deployment. Several themes emerged from our review of studies; these are presented below.

4. Results

4.1 Overview of Included Evidence

From 2020 to 2025, the range of methods has increased. Initially, researchers used data from public or small local databases. Later, in Saudi Arabia, researchers used electronic health records data and obtained more desirable results in terms of disease onset, risk prediction, and early diagnosis. Most of the studies in disease-focused research use tree-based ensemble algorithms for their examination. In diabetes diagnosis, researchers have used random forest plus XGBoost more than other machine learning models. This is because these models are more robust in dealing with non-linear connections in data and are more suitable for dealing with different types of data and missing data. They have also shown higher performance in comparison to other models in tasks related to diabetes.

4.2 Diabetes – Early Risk Identification and Onset Timing

In the case of diabetes research in Saudi Arabia, the emphasis has moved from classification to more relevant issues, such as who might acquire the condition earlier and what might be the signal for its development. A study on the age of onset of type 2 diabetes in Saudi Arabia used ML, comparing regression and ML models, and concluded that the performance of the random forests and well-transformed linear models was excellent. Another study on the development of type 1 diabetes in children and young adults using the case-control method of ML identified some of the possible signals for the onset of the condition. ML methods are effective in the early detection of type 2 diabetes in a large group of people who share similar characteristics and strong discriminative ability. Common predictors include age, BMI, fasting glucose, HbA1c, where available, triglycerides, HDL/LDL, blood pressure, and lifestyle/medication proxies. Feature space reduction and interpretation are increasingly aided by feature selection techniques such as chi-square, information gain, and forward selection. Notably, calibration is rarely reported, as well as error rates by groups such as gender, geography, and comorbidities are rarely explored, which is important for prevention-oriented applications.

4.3 Cardiovascular disease: Risk stratification and early diagnosis support

In cardiovascular disease, the work of the models is to operate on two tracks at once, supporting early diagnosis by estimating the likelihood of disease given common traits, as well as making predictions regarding the near-to mid-term evolution of a patient's state or likelihood of occurrence. One important model, highlighted for the 2025 target, is the focus on ethics, where the need to be transparent, interpretable, and free of bias is paramount, along with the selection of features to be used, as well as the evaluation of different ensemble models. This is particularly relevant to the context of Saudi Arabia, where the research is highly applicable, providing clear steps to be taken, such as cleaning the data, selecting the right features, comparing the models, and addressing the issue of ethics. Common features that are modeled include age, sex, blood pressure,

cholesterol, smoking, diabetes, among others, as these are known to be factors that lead to cardiovascular disease, particularly in the context of Saudi Arabia/Gulf region research. Some research compares hybrid models that combine structured data from electronic health records with other data types, although for early detection, the best option is to utilize a known tabular model. Overall, across all cardiovascular studies, there is a lack of external validation, and there is a tendency for model performance to degrade in a new setting or over time due to coding, lab, and patient population issues. While there is a relatively consistent level of reporting for relative performance to STARD-AI and TRIPOD-AI, there is less frequent reporting of calibration, decision curve analysis, and prospective impact studies.

4.4 Cancer: structured data for early warning and referral support

In Saudi Arabia, there is a greater dependence of risk prediction models for cancer, compared to diabetes and cardiovascular disease, on imaging data from radiology and pathology. Yet, from a global perspective, machine learning models based on structured data can be effective in predicting risk sufficiently in advance to prompt investigations by primary care. This is particularly important in identifying those individuals in a population who should be considered for a screening test to detect future problems. It is also important in diagnosis, where structured data can be used to identify individuals in a population who should be referred for a test earlier than they would be otherwise. This is particularly useful in a Saudi setting, where there is a need to improve screening programs.

4.5 Cross-cutting technical themes

Validation and generalization. There is typically validation of data splits over time, similar to how we expect to use the system in practice.

Calibration. Model probability calibration is important. There is still debate about calibration plots, scores, and methods.

Interpretability. There is some consideration of feature importance in tree-based models and coefficients in regularized regression. While these are standard considerations, there is relatively little discussion of interpretation of predictions, especially for structured data in Saudi Arabia. Interpretation of predictions is vital for trusting predictions in medicine.

Fairness. There is little consideration of how well the model performs for different groups based on factors like sex, age, region, socioeconomic status, etc. This is surprising and especially relevant for false negatives. Data quality issues and missing data. There are missing data points in most datasets used for ML in medicine, especially coding scheme issues.

5. Discussion

5.1 Interpretation in the Saudi context

The shift from traditional medicine and more towards digital health in terms of ML for early detection is a major step forward for ML in Saudi Arabia. This is a positive step forward for ML in Saudi Arabia. It is important that traditional medicine keeps advancing in parallel with ML. Most interactions with patients will have features that are important for stratifying patients for early detection.

The question is not whether ML makes a prediction; the question is whether ML makes a prediction that is better than current predictions without compromising fairness and equity and without contributing to alert fatigue. Diabetes models that can predict the onset or progression can link with evidence-based prevention strategies. For those at risk, nutritional education programs and monitoring can be conducted. Cardiovascular models can guide prevention therapies or lead to further investigations. Cancer models based on structured data can serve as a safety net for primary care and help identify abnormal signs, symptoms, and lab results for further evaluation.

5.2 Proposed Translational Framework

A stepwise approach from simple to complex models can be proposed as follows:

- 1) Data readiness – data dictionary, standardization, profiling, and bias detection.
- 2) Model building – from simple models such as regularized logistic regression to more complex models such as ensembles, feature selection, and clinically relevant prediction horizons.
- 3) Validation – simple temporal validation and moving on to external validation and recalculation.
- 4) Safety and fairness – performance evaluation, subgroup analysis, and error analysis with a focus on safety issues such as false negatives.
- 5) Workflow – user experience optimization, workflow integration, and detailed documentation of the interaction between humans and AI models.

6) Monitoring – drift detection and monitoring with periodic revalidation.

This proposed framework also aligns with current reporting and evaluation standards for AI models such as TRIPOD-AI, STARD-AI, and prospective evaluation.

5.3 Practical Model Design Considerations

Feature Sets. In the case of early detection, the feature set should consist of simple and readily obtainable features. Models based on rare tests might not cover all the entire population and might also fail to cover the population that does not have adequate resources.

Algorithms. Gradient boosting and random forests are effective in discrimination for tabular data, such as EHRs. Regularized logistic regression is another effective and simple method that can be used for discrimination, and it also calibrates well. An ensemble method can also be used.

Clinical Thresholding. The threshold decisions should be made using decision-analytic methods, including net benefit and calibrated risk, rather than focusing on maximum accuracy.

5.4 Ethical, Legal, and Social Considerations

There are chances that the models used for early detection might direct more resources towards the population at higher risk, and this might exacerbate the current inequalities. The use of AI models in Saudi Arabia should ensure subgroup evaluation, documentation of the use and non-use of the models, privacy-preserving data practices, and auditing. The current ML research on cardiovascular disease focuses on interpretability and fairness, and these are not optional.

5.5 Research Gaps

- 1) Prospective validation in live environments.
- 2) Calibration.
- 3) Risk prediction for cancer using structured data in Saudi Arabia.
- 4) Fairness and distribution shifts.

5.6 Saudi Implementation Blueprint: From Promises to Proven Results

The way forward is a simple, balanced plan that delivers on promises, turning them into actual results. It is a combination of good health analytics and a healthcare system that is prepared to produce actual results.

Basic Data Readiness Package

Each participating system/hospital will be provided with a basic data readiness package. This will include a data dictionary, a standard coding scheme such as ICD/SNOMED for diagnoses and procedures, standard lab data, and a mechanism for aggregating visits and outcome codes. In order to keep up with the evolving chronic disease risk, cohorts will be developed with precise index event dates, as well as well-defined look back and look forward windows. For instance, 6 to 12 months to track changes in diabetes risk, 1 to 3 years to track cardiovascular risk factors, and shorter time frames to track shifts in cancer referral probabilities. And, as the saying goes, “if you can’t measure it, it isn’t important.”

Modeling Approaches

Use the approaches that are appropriate for your problem. For simple, reliable performance on tabular EHRs, regularized logistic regression is a good choice. Gradient boosting, XGBoost, and LightGBM are also good choices, although they are not necessarily easily interpretable. Simple models can be used to validate more complex models. Thus, feature engineering grounded in clinical reality would involve focusing on trends and variability rather than repetition, using current data, and using medication proxies to estimate the intensity of treatment. The severity of disease can be estimated by using a comorbidity index. In the context of clinical reality, the explainability and actionability of the feature are important, and though global feature importance and partial dependence plots are useful, individual-level features are more important for decision-making. Temporal validation and cross-validation by geographic clusters, i.e., central, western, and eastern regions, are also important, and decision curve analysis, weighing benefits against system capacity and screening volume, also plays a role.

Integrating with Workflow and Governance

To ensure the smooth operation of the clinical decision support system, the system should specify who gets alerted, what gets done, and what gets documented, and this can start by implementing a silent pilot where the alerts are generated but not displayed to anyone, and then rolling it out gradually, eventually moving towards prospective validation using pragmatic trials, e.g., a stepped wedge design, and the discrimination ability of the model, i.e., AUC, and process and patient outcomes, and the digital health best practices from Saudi Arabia should be translated into tangible improvements.

Operational and Governance Details

To specify the operation, data lineage, version control, rollbacks, and accountability in case of any adverse outcome, and the patient registries should be a central focus to improve the results, including patient participation and informed consent for the use of AI in preventive care.

6. Limitations

This review also has some limitations, and the first one is the differences in the evaluation and results of the studies on the use of AI, which makes it difficult to perform a quantitative evaluation of the studies on the use of AI. Another limitation is the possibility of the studies on the use of AI being positive, and the possibility that there are new and innovative methods that are not included in the academic studies.

7. Conclusion

Making use of AI to identify health issues at their earliest stages, based on day-to-day clinical data, is becoming more feasible in Saudi Arabia. This may help in the prevention and early detection of diabetes, heart disease, and some cancers. In the short term, the most promising course of action is to develop strong, well-governed prediction pipelines that are effective in handling time-related data, including calibration and time-related validation, and are seamlessly integrated into clinical workflows. In order to make a real difference at the national level, it would be important to ensure that the programs from Saudi Arabia put emphasis on external validation, fairness, and prospective impact studies, all of which are based on modern AI reporting standards. In order to make sure that predictions result in real improvements in care, it would be essential to ensure that there is collaboration between clinical teams, data teams, and informatics teams. In addition to that, it would also be important to report uncertainty, monitor model drift, and recalculate as disease prevalence and care pathways change. Finally, it would also be important to make sure that data schemes are transparent in order to boost reproducibility and to ensure that the effectiveness of these tools in other Saudi healthcare systems can be evaluated.

Table 1. Evidence snapshot of Saudi-relevant routine-data AI early detection studies (2020–2025).

Disease focus	Setting / data	Outcome / horizon	Model family	Key predictors (examples)	Validation	Key gap
Diabetes	Hospital EHR cohort (KSA)	Age at onset / risk timing	RF, SVR, ANN, MLR	Lipids, BMI, SBP, vitamin D	Internal split	Calibration & external validation limited
Diabetes (T1D)	Saudi case-control (children)	Development risk indicators	ML classifiers	Clinical indicators, labs	Case-control eval	Generalizability beyond site
CVD	UCI-style + translational framing	Early diagnosis support	XGBoost, RF, DT, LR	Age, BP, cholesterol, ECG proxies	Train-test + CV	Real-world workflow evaluation
Cancer (general)	Primary care symptoms + labs (global)	Short-horizon cancer risk	Ensembles / regularized models	Age, symptoms, blood tests, utilization	Temporal & external (varies)	Saudi cohort scarcity for structured data
Diabetic retinopathy	Fundus imaging (global)	Severity grading	CNN / DL	Image features	External datasets	Structured-data risk prediction underused

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