A Comparative Analysis of Cardiovascular Disease Risk Assessment Frameworks in India and Abroad: Focus on Framingham and Score Based Models

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ABSTRACT

SCORE and its updated version, SCORE 2, have been largely centered in Europe and focused on predictive schemes for fatal CVD events; they do not have any validation from Indian populations due to a shortage of longitudinal data (Kasim et al., 2023). The WHO/ISH charts, popular in resource-limited settings for their simplicity, underperform in identifying risks in young adults and women (Selvarajah et al., 2014). Depending mostly on conventional risk factors, these models don't include social determinants of health such as education, income, occupational stress, air pollution, and localized dietary habits, all of which shape India's CVD profile (Prabhakaran et al., 2016; Mathur et al., 2024). There is still insufficient representation of rural populations, and apart from that, these models suffer a practical dead-end: low clinical adoption, digital integration, as well as patient engagement have greatly hindered implementation.

While there remain prevention prospects under Ayushman Bharat and NPCDCS, a lack of a dynamic, India-specific CVD risk tool is certainly denying the country an effective population-level screening-means and intervention. While FRS and SCORE provide valuable foundations, their limitations in the Indian context necessitate development of inclusive, data-driven, and locally validated frameworks to better manage and reduce the country's growing CVD burden.

Keywords- Cardiovascular disease, Framingham risk Score, SCORE 2, India, risk prediction models, systematic review.

INTRODUCTION

Cardiovascular diseases (CVDs) represent today's major global problems heavily burdening low- and middle-income countries such as India. According to the WHO (2021), globally, about 31% of deaths are due to CVDs, with ischemic heart disease and stroke accounting for the majority. In India, it is growing further with urbanization, demographic changes, sedentary behaviors, dietary changes, and a lack of very basic health literacy (Prabhakaran et al., 2016). In the last few decades, cardiovascular risk assessment tools like the Framingham Risk Score (FRS) and SCORE have been in the forefront of preventive strategies worldwide. These frameworks divide people into risk categories based on risk factors to initiate interventions for those in greater risk and resource utilization for those in lesser risk (Rodondi et al., 2012). However, these models are said to have been formulated in Western setups and are thus not believed to characterize risk pathways of a country like India adequately (Artigao-Rodenas et al., 2013). India has a diverse range of CVD risk profile based on regional and socioeconomic differences. Hypertension and dyslipidemia pose a great risk in urban areas, while malnutrition and inaccessibility to health care pose serious challenges in rural areas (Gupta et al., 2019). Despite this, global models are often applied uniformly, leading to inaccurate individual risk assessment.

Due to high out-of-pocket healthcare costs in India, accurate risk prediction is of utmost importance. According to the Indian Council of Medical Research (ICMR), more than half of the households suffering from CVD are facing catastrophic expenditures and often end up falling into poverty (Mathur et al., 2024). Proper stratification could assist in preventive measures aimed at reducing the financial load on both the households and the system.

FRS uses clinical variables to estimate the 10-year risk of CVD but does not provide consistent results in the Indian phase, especially in women and rural populations (Gupta et al., 2019; Kulothungan et al., 2024). SCORE, which has been developed for
Europe, is practically rendered useless in India due to the absence of robust mortality data representative of the Indian population (Kasim et al., 2023). The WHO/ISH charts work well in resource-poor settings because of their simplistic format but tend to underestimate risk for young people and females (Selvarajah et al., 2014). Another disincentive in applying these are several India-specific risk factors for CVD: air pollution, stress, and dietary diversity. While staying on the global discussion, it is worth mentioning the lack of centralized CVD data systems and absence of long-term cohort studies in India. Most of the research is carried out on cross-sectional data, thus limiting model development and integration with advanced AI tools now being used globally for CVD prediction.

Programs like Ayushman Bharat and NPCDCS are reflective of an increased policy focus on NCDs. Despite these efforts, without a validated risk assessment model tailored to the Indian population, there is still some difficulty encountered in timely identification and management of high-risk individuals, especially given India's demographic diversity and dual burden of malnutrition. This review goes on to evaluate the FRS and SCORE models with respect to their validation in India and their relevancy in practice. It pinpoints some critical gaps- the lack of rural inclusion, poor integration of social determinants, and logistical impediments to deployment. It advocates the development of a homegrown, flexible CVD risk model that fits India's epidemiological scenario and can be updated in real time through digital interfaces. The next sections go into the details of model evolution, their recalibration in India, and suggestions on how to create a scalable, evidence-based solution.

METHODOLOGICAL GAPS AND DATA LIMITATIONS IN INDIAN CONTEXT

Although the amount of research on predicting the risk of cardiovascular disease (CVD) in India is increasing, there are still a number of methodological and data-related issues. In the Indian context, these gaps impede the creation, verification, and application of risk prediction models like the WHO/ISH charts, SCORE, and Framingham Risk
Score (FRS). The serious flaws in data infrastructure, research techniques, population representation, and contextual adaptation that impact the reliability and applicability of CVD risk models in India are explained in detail in this section.

A. Absence of Outcome-Based and Longitudinal Cohort Data

The lack of extensive, nationally representative longitudinal cohort studies that monitor cardiovascular events over time is one of the most urgent problems. The majority of research conducted in India employs cross-sectional designs, which are insufficient for developing risk models that depend on time-to-event analysis (Gupta et al., 2019). The CARRS and ICMR-INDIAB studies, for instance, offer insightful information about the prevalence of risk factors, but they do not have the longitudinal follow-up required to confirm model predictions against actual results. Furthermore, the few cohort studies that are available frequently have short follow-up periods, small sample sizes, and urban biases. This makes it difficult to accurately estimate baseline survival functions or derive robust hazard ratios for different risk factors, both of which are essential for developing risk scores (Kulothungan et al., 2024).

B. Under-representation of Low-Income, Female and Rural Populations

Research on CVD risk prediction rarely takes into account India's diverse population. Because the majority of current models are based on urban-centric cohorts, they are not well generalizable to tribal and rural populations, which have different risk profiles influenced by occupational factors, under nutrition, and occupational hazards, limited healthcare access, and low literacy (Mathur et al., 2024). Due to cultural barriers, caregiving responsibilities, and lower participation in health surveys, women are also underrepresented, particularly in rural areas. As a result, in these populations, the recalibrated models frequently perform poorly. For example, lipid-based models such as FRS had significantly lower predictive accuracy in rural female cohorts, according to Kulothungan et al. (2024). In addition to compromising model accuracy, this lack of inclusivity maintains health disparities.

C. Inadequate Social and Environmental Determinant Integration

Clinical and behavioral factors like blood pressure, diabetes, smoking, and cholesterol levels are the main components of traditional risk models. Though they are rarely included in models, social determinants like education, income, occupation, and whether a person lives in an urban or rural area have a significant impact on cardiovascular risk in the Indian context (Prabhakaran et al., 2016). Additionally, standard models usually do not include environmental exposures like air pollution, which has been strongly associated with cardiovascular morbidity and mortality. With fine particulate matter (PM2.5) consistently surpassing WHO thresholds in Indian metropolises like Delhi, this omission is noteworthy (Mathur et al., 2024).

D. Variability in Data Gathering Techniques

Different studies employ different data collection techniques for the creation and validation of risk models. Model reliability is impacted by discrepancies brought about by different definitions of hypertension, diabetes, and hyperlipidemia as well as different measurement tools and procedures. Furthermore, a large number of studies use selfreported data, which are vulnerable to underreporting and recall bias, particularly when it comes to family history, alcohol consumption, and smoking. Additionally, many Indian studies' outcome adjudication is deficient in standardization. Hospital records, verbal autopsies, or insurance claims are often used without clear criteria, leading to potential misclassification of cardiovascular events.

E. Limited Use of Modern Predictive Analytics

For risk estimation, the majority of Indian studies use conventional statistical models like logistic regression or Cox regression. Despite being well established, these might not fully capture the intricate, non-linear relationships between variables that are typical in a variety of populations. In Indian research, advanced techniques like artificial intelligence (AI) and machine learning (ML), which can increase model accuracy through feature selection and iterative learning, are rarely employed (Kasim et al., 2023). The lack of digital infrastructure and qualified staff in many public health organizations and research institutions further widens this technological divide. Incorporating CVD risk models into mobile health (mHealth) platforms or electronic health records (EHRs) that could support real-time risk estimation has not received much attention.

F. Absence of Model Calibration and External Validation

The agreement between expected and observed risk is referred to as calibration, and testing a model in a population other than the one used for development is known as external validation. Both are essential for determining a model's generalizability. However, Indian studies frequently omit or report these steps insufficiently (Gupta et al., 2019). For example, the CARRS study's recalibrated FRS demonstrated better discrimination, but it lacked calibration assessment in female or rural cohorts. Confidence in the results is also limited because the majority of studies do not use external validation with datasets from other regions.

G. Institutional and Policy-Level Obstacles

Even when robust models are developed, their use in clinical and policy contexts is constrained by institutional inertia and fragmented health governance. The use of standardized risk scores in primary care settings is not required by any single national policy. Therefore, rather than using evidence-based methods, risk assessment frequently relies on ad hoc clinical judgment. The operationalization of risk scores at scale is further complicated by the dearth of decision-support tools, training for frontline health workers, and funding for preventive screening initiatives.

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H. Concerns about Data Privacy and Ethics

Large-scale health data, such as insurance databases and digital health records, are becoming more and more important in the development and validation of risk prediction models. But India doesn't have a strong legal framework for data privacy and ethical use of health information. This raises concerns about informed consent, data sharing, and potential misuse, which can deter both institutions and individuals from participating in such initiatives.

I. Fragmentation of Research Efforts

Another major methodological limitation is the siloed nature of cardiovascular research in India. Studies are often conducted independently by academic institutions, state governments, or NGOs, with minimal coordination or data sharing. This leads to duplication of effort, missed opportunities for meta-analysis, and a lack of cohesive policy recommendations.

J. Conclusion of Methodological Gaps Section

A multifaceted approach is necessary to improve cardiovascular risk prediction in India. First, infrastructure for longitudinal cohorts that capture a variety of population segments needs to be invested in. Second, emphasis should be placed on standardizing definitions, measurement procedures, and outcome adjudication. Third, it is necessary to formalize the incorporation of behavioral, environmental, and social determinants into risk models. Model robustness can be further increased by implementing contemporary predictive technologies like AI/ML, which are made possible by better digital infrastructure and data governance frameworks. Lastly, putting research into practice requires policy alignment and coordination at the national level. For the creation of an indigenous, scalable, and precise cardiovascular risk prediction framework that meets the particular requirements of the Indian population, these gaps must be filled.

IMPLEMENTATION CHALLENGES AND REAL-WORLD USE OF RISK SCORES IN INDIA

There are a number of practical implementation issues with integrating cardiovascular disease (CVD) risk prediction models into clinical practice in India. These obstacles include gaps in healthcare worker training, policy-level restrictions, infrastructure shortcomings, and digital integration constraints. The limitations of using risk scores like FRS, SCORE, WHO/ISH, and RPCE within Indian health systems are examined in this section, which is based on empirical findings and public health analyses.

A. Insufficient Physician Knowledge and Education

The lack of knowledge and training among healthcare professionals, especially in public sector settings, is a significant obstacle to the adoption of risk scores. Primary care physicians and general practitioners frequently don't know how to use cardiovascular risk prediction tools or how to interpret their results when making clinical decisions (Gupta et al., 2019). Concepts like absolute risk, which are not frequently stressed in medical curricula or continuing medical education, are necessary for risk models like FRS and SCORE.

Furthermore, time-consuming evaluations are discouraged in Indian public health clinics due to the overwhelming workload and patient volume. Treatment for symptoms may be given precedence over preventative measures by providers. As a result, models are underutilized even in cases where they are available.

B. Inadequate Health Infrastructure

In India, primary health centers (PHCs) frequently lack the resources necessary for basic diagnostic tests like lipid profiling, which are necessary for the majority of risk prediction models. Although nonlaboratory-based

WHO/ISH charts offer an alternative, they still rely on blood pressure checks and diabetes screening, which are services that are not always offered at the PHC level and compromise accuracy for convenience (Mathur et al., 2024). Furthermore, the majority of PHCs do not use decision-support software or electronic medical records (EMRs). On the other hand, risk scores have been incorporated into EMRs in many Western nations, enabling real-time risk assessment and notifications. Implementation is made more difficult by India's lack of such digital systems.

C. Barriers at the Patient Level and Behavioral Economics

The effectiveness of risk scores, even when they are used, is dependent on patient participation and adherence. If a person is classified as high-risk, they must change their lifestyle or take medication. However, because of cultural beliefs, financial limitations, or low health literacy, patients often do not follow recommended interventions. According to a study by Kulothungan et al. (2024), people in Tamil Nadu who were classified as high risk according to the WHO/ISH chart hardly ever changed their lifestyle or took their medications as prescribed unless they received intensive counseling. This emphasizes the necessity of interventions informed by behavioral economics to supplement technical tools.

D. Inadequate Inclusion in National Health Programs

There is no established procedure for utilizing validated CVD risk scores in programs such as the National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Diseases, and Stroke (NPCDCS), despite the fact that these initiatives seek to incorporate preventive screening. Practices are fragmented as a result of wide variations in state-level implementation. Preventive screenings could be provided on a large scale by the Ayushman Bharat Health and Wellness Centres (HWCs). However, opportunities for early intervention are lost because standardized risk stratification tools are not yet integrated into service delivery protocols (Prabhakaran et al., 2016).

E. Data Entry and the Digital Health Ecosystem

Difficulties Potential platforms for incorporating risk scores are provided by digital tools such as the Comprehensive Primary Healthcare (CPHC) application under Ayushman Bharat. Nonetheless, issues with inconsistent internet access, data entry errors, and platform incompatibilities still exist. The ability to gather, monitor, and evaluate cardiovascular risk scores at the population level is further constrained by the lack of a single electronic health record system that unites public and private providers.

F. ASHA Employees' Role in Community Health Interventions

When it comes to outreach for preventive care, Accredited Social Health Activists (ASHAs) are essential. They lack training on how to apply risk scores, though. It might be revolutionary to incorporate streamlined risk prediction tools into ASHA processes, perhaps via mobile applications. This has been investigated in a few pilot studies.

G. Actuarial Use and Health Insurance

Preventive benefit design and risk-based premium pricing in health insurance are two areas where risk prediction models show promise. Nonetheless, the insurance industry in India is still primarily reactive, emphasizing treatment over prevention. Although it would necessitate data sharing agreements and privacy frameworks that are not yet in place, a recalibrated Indian risk model incorporated into insurance underwriting could increase affordability and fairness (Kasim et al., 2023).

H. Section on Implementation Conclusion

In India, the use of cardiovascular risk scores is hampered by structural, behavioral, and systemic issues. To solve these problems, cooperation between the fields of digital technology, community health, policy, and health systems will be required. Unless risk models are integrated into processes, backed by digital resources, and strengthened by public health initiatives, they are insufficient on their own. The policy implications and suggestions for creating a long-term, India-specific cardiovascular risk prediction framework are examined in the following section.

POLICY IMPLICATIONS AND FRAMEWORK FOR INDIGENOUS MODEL DEVELOPMENT

The prevalence of cardiovascular disease (CVD) in India makes a strong case for developing and deploying a domestic, reliable, and expandable risk prediction system. When applied to Indian populations, imported models such as the WHO/ISH charts, SCORE, and Framingham Risk Score (FRS) have serious contextual limitations, as was mentioned in the preceding sections. Therefore, the creation of a nationally validated risk assessment tool is urgently needed in order to move away from reliance on Western-calibrated models. The main policy implications are discussed in this section, along with a framework for creating an indigenous model that takes into account India's socioeconomic, epidemiological, and healthcare infrastructure realities while also referencing global best practices.

A. Acknowledgment of Predicting CVD Risk as a Public Health Priority

India's national health policy needs to clearly acknowledge CVD risk stratification as a fundamental preventive care tool. Although the NPCDCS program and the National Health Policy (2017) emphasize managing NCDs, there is no requirement to use evidence-based risk models. To make risk prediction a required first-line screening method in both public and private primary healthcare, a change in policy is required.

B. Establishing a Database for National Longitudinal Cohorts

One essential prerequisite for developing a predictive model is the availability of high-quality, longitudinal data. Investments in a national CVD cohort that represents a variety of age groups, socioeconomic backgrounds, and geographic locations are imperative for India. Cohort members ought to be monitored for at least ten years using validated endpoints to track risk factors and CVD events. This will make it possible to derive and recalibrate indigenous models with high predictive value based on data. To enable pooled analysis, the proposed cohort should harmonize data standards and incorporate data from existing sources, including CARRS, ICMR–INDIAB, NFHS, and private registries. Model validation and iterative updates should be supported by a centralized data repository that is subject to ethical and privacy frameworks.

C. Combining Environmental and Social Factors

The majority of Western risk models overlook elements that are crucial to Indian health outcomes, such as psychosocial stress, urban-rural disparities, poverty, education, and air pollution. Social vulnerability variables (e.g., caste, occupation), dietary habits, non-cigarette tobacco use (e.g., bidi, chewing tobacco), and exposure to biomass fuel should all be included in the indigenous model. A more comprehensive model that is more in line with the Indian context can be produced by collecting these variables via digital health platforms, community surveys, and satellite data (for example, environmental risk exposure).

D. Using AI and ML to Predict Dynamic Risk

India's domestic model should make use of artificial intelligence (AI) and machine learning (ML) to account for the diversity of risk factors and health profiles. These technologies can discover nonlinear relationships between variables, adjust to regional variations, and learn dynamically from new data. In cardiovascular risk prediction, ensemble approaches and neural networks have outperformed conventional regression-based tools (Kasim et al., 2023). Model co-development and pilot deployment can be facilitated by collaborations with academic institutions, AI startups, and public health organizations. Personalized, context-sensitive risk reduction recommendations for patients and providers can also be produced by AI-powered platforms.

E. Mandatory Policy for Primary Healthcare Integration

Government health programs like Ayushman Bharat, Health and Wellness Centers (HWCs), and the eSanjeevani telemedicine platform need to incorporate the indigenous risk model. To facilitate door-to-door risk screening, a straightforward smartphone interface connected to the indigenous model can be created for frontline employees, such as ASHAs and ANMs. Risk prediction tools must be incorporated into service procedures, along with required documentation and referral policies for high-risk individuals, in order to guarantee adoption. Data synchronization and automated follow-up alerts will be made possible by integration with the Comprehensive Primary Health Care (CPHC) platform.

F. Building Capacity and Training Workers

For the risk model to be implemented effectively, healthcare professionals at all levels—including physicians, nurses, and ASHAs—must be trained in its use. The development and integration of standardized training modules into nursing and MBBS programs, as well as online CPD (Continuing Professional Development) platforms, is imperative.

Co-designing educational resources that take into account local knowledge and obstacles is another benefit of community-based participatory research. Visual infographics, for instance, can be used to make risk interpretation easier for populations with low literacy levels.

G. Funding and Incentive Systems

It will be necessary to invest in digital infrastructure, training for human resources, and screening materials in order to implement the indigenous model. When it comes to funding and scaling, public-private partnerships can be extremely important. By offering premium subsidies, insurance companies can be encouraged to incorporate the risk model into their underwriting and preventive care practices. Using risk stratification tools, states could also receive performance-based grants linked to CVD screening goals and follow-up adherence.

H. Tracking, Assessing, and Model Development

Key performance indicators like sensitivity, specificity, decrease in the incidence of CVD, cost-effectiveness, and patient adherence should be included in a strong framework for evaluating the model. Accountability will be guaranteed by routine audits and independent validations. The model ought to be made to adapt to fresh data and user input. It is necessary to institutionalize version control and open reporting of model updates (such as recalibration based on updated datasets). Additionally, this will encourage worldwide publication and WHO approval for wider use in South Asia.

I. Considerations for Data Governance, Ethics, and the Law

Consent, transparency, and data ethics must all be incorporated into risk prediction models. It is necessary to clarify and enforce data privacy laws, particularly those pertaining to digital health data. In order to prevent commercial monopolization, access to the model and related tools should be fair and supported by the government.

J. Policy Framework Section Conclusion

In conclusion, an indigenous, data-driven, and policy-anchored risk prediction framework is required due to the prevalence of CVD in India. Such a model needs to be integrated into primary healthcare delivery, driven by contemporary analytics, and take into account India's socioeconomic realities. This model has the potential to become a pillar of CVD prevention and health equity in India with sufficient investment in digital tools, training and data infrastructure.

CONCLUSION

According to our review, Framingham Risk Score (FRS) has been widely modified and recalculated worldwide, including in India; however, when applied to Indian subpopulations, its predictive accuracy is still only moderate. Additionally, the majority of recalibration attempts have been geographically restricted and have not included the required external validation, follow-up period, and consideration of India's vast socioeconomic diversity. The comparative analysis also showed that SCORE and WHO/ISH charts frequently underestimate risk in women and younger adults, despite being easier to use in environments with limited resources. The insufficiency of current instruments to represent India's distinct risk factor profiles, including common non-traditional hazards like air pollution, psychological stress, and dietary changes, is a significant finding. Furthermore, the creation and use of reliable predictive models are still hampered by infrastructure constraints, which range from a lack of standardized longitudinal data to inadequate digital integration.

Training healthcare professionals, incorporating models into national health programs like NPCDCS and Ayushman Bharat, and guaranteeing follow-up care for high-risk individuals are all crucial, according to the analysis of implementation challenges. A multi-tiered strategy is required, which includes building a comprehensive national cohort database, integrating environmental and social determinants, utilizing AI/ML techniques, and making sure the model is deployed across digital and community health platforms. Preventive cardiovascular care in India could undergo a revolution with an inclusive, data-driven framework backed by community involvement, public health infrastructure, and continuous evaluation.

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