From data to diagnosis: Revolutionising cardiovascular risk assessment in Sri Lanka with artificial intelligence

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Abstract

There are no cardiovascular risk prediction models designed explicitly for Sri Lankans. As a result, we are relying on risk prediction models developed for white Caucasians or the Southeast Asia region (SEAR) to risk-stratify Sri Lankans. Our research has shown that risk predictions from different models can vary significantly. None of the risk prediction models has been validated for the Sri Lankan population, a gap we addressed in 2019. The findings demonstrated that the predictions of the World Health Organisation (WHO-SEAR) risk charts were effective for low-risk individuals but less sensitive for high-risk individuals and women.

Therefore, we aimed to develop a risk prediction model specific to Sri Lankans, using data from a cohort followed up for 10 years as part of the Ragama Health Study. We applied machine learning (ML) to the dataset and found that the predictions generated by artificial intelligence are more accurate than those provided by the WHO risk charts. Subsequently, we developed a new ML-based risk prediction model for Sri Lankans, named the SLCVD score, along with an online risk calculator for practical use, even in rural areas of Sri Lanka. Furthermore, this new model was validated in an external cohort of hospital-based patients, demonstrating that it is more effective at identifying high-risk individuals in Sri Lanka than the WHO model. We further refined the model for generalizability using nationally representative data from the STEPwise approach to surveillance (STEPS) survey conducted in 2021. This risk calculator will be launched through the Ministry of Health for free usage once we secure the patent rights.

Accurate risk prediction is crucial for implementing primary preventive measures in a "High-Risk strategy" to ensure they are cost-effective. This approach is especially important in resource-limited settings like Sri Lanka.

Key words: cardiovascular risk assessment, Sri Lanka, artificial intelligence, World Health Organisation risk charts, Southeast Asia region

Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally and account for around 32% of all global deaths. Of these, 85% are due to heart attacks and strokes.[1] CVD is also one of the top three causes of disability-adjusted life years in the world.[2] One-third of CV deaths occur prematurely in people under 70 years of age, affecting the workforce of a country. More than three-quarters of cardiovascular (CV) deaths take place in low- and middle-income countries. More than 80% of deaths in Sri Lanka are due to noncommunicable diseases (NCDs), and ischaemic heart disease is the most common cause of hospital deaths in Sri Lanka, accounting for around 23%.[1,3]

Ninety per cent of CVDs are linked to modifiable risk factors, and most cardiovascular diseases can be prevented by addressing behavioural and environmental risk factors.[4] Prevention of CVD is more cost-effective than treatment for several reasons:

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established treatment options for CVDs are expensive, treatments may not be curative, and some CVDs occur suddenly, leaving little or no time to seek medical help.[5,6,7] Therefore, the most effective way to reduce the CVD burden in a low-middle-income country like Sri Lanka is to manage cardiovascular risk factors actively.

Risk factors usually cluster and interact multiplicatively, increasing an individual's CV risk.[8] Individuals with high CV risk have a greater absolute risk reduction with treatment than those with moderate to low CV risk. Therefore, the benefit of interventions is greater in individuals with high CV risk.[9] Therefore, controlling risk factors to achieve treatment targets based on one's absolute CV risk is more cost-effective than basing it solely on individual risk factor levels, such as in treating hypertension, considering the total CV risk rather than going only by the blood pressure value.[10] Moreover, implementing preventive measures targeting at-risk populations (high-risk strategy) is more cost-effective than implementing for the total population (population-based strategy), as the high-risk strategy minimises costs as well as medication-related side effects.[11] As such, most of the latest national and international NCD guidelines recommendations are based on an individual's 10-year CV risk. Therefore, it is essential to calculate the total CV risk of individuals before initiating primary preventive measures.

Calculating the total CV risk requires reliable risk-prediction models to identify individuals with high CV risk without misclassifying. However, no risk prediction models are derived from Sri Lankan cohorts or explicitly developed for Sri Lankans. Therefore, Sri Lankan physicians use freely available CV risk prediction models to predict the CVD risk of Sri Lankans. Still, they are either the models developed for the whole of the Southeast Asia Region (SEAR), like the World Health Organisation (WHO) risk charts or the models derived from White Caucasians, like the Atherosclerotic Cardiovascular Disease risk (ASCVD) calculator, Systematic Coronary Risk Evaluation (SCORE) charts and Framingham general cardiovascular risk score (FRS). However, the CV risks of different populations differ with genetics, ethnicity, diet, lifestyle, socio-economic status, etc. The WHO (SEAR) risk charts are developed for the Southeast epidemiology region, including Indonesia, Cambodia, Laos, the Maldives, Myanmar, Malaysia, the Philippines, Thailand, Timor-Leste, Vietnam, Mauritius, the Seychelles, and Sri Lanka.[12] These countries' socioeconomic and cultural backgrounds differ from those of Sri Lanka; therefore, the WHO (SEAR) risk charts may not accurately predict Sri Lankans' CV risk. On the other hand, none of the risk prediction models were validated among Sri Lankans until we did it in 2019.[13]

Rationale and objectives

Therefore, selecting the best risk-prediction model to identify high-risk Sri Lankans reliably is crucial. Developing a new risk prediction model specific to Sri Lankans would be ideal.

Therefore, I aim to answer these outstanding research questions in this oration.

1. To compare the CV risk predictions of a Sri Lankan cohort using different prediction models to study the agreement between models
2. To describe the validation of the WHO risk charts in a Sri Lankan cohort
3. To present an experiment in predicting the CV risk of Sri Lankans using artificial intelligence
4. To present the development of a CV risk prediction model specific to Sri Lankans

Methods, results and discussion

Research question 1

We calculated 10-year CV risk predictions of the patients who attended a medical clinic at the Faculty of Medicine, Ragama, over 4 months in 2017. Ethics approval for the study was obtained from the Ethics Review Committee (ERC) of the Faculty of Medicine, University of Kelaniya (P/18709/2018). We calculated CV risk using the Framingham risk calculator and the WHO/ISH (2006) risk charts in the selected sample. We compared the percentage with high CV risk (≥20%) across models to assess agreement. Both the FRS and WHO/ISH charts are intended to predict the same measure: the "10-year risk of a major fatal or non-fatal CVD". Therefore, predictions should ideally be equal when calculated using either of the two risk scores.

We selected individuals without prior cardio-vascular disease and calculated FRS and WHO/ISH risk predictions using cholesterol-based (lab-based) and BMI-based (non-lab-based) models. We categorised them into low (<20%) and high (≥20%) risk groups based on their risk scores. We compared the agreement in risk categorisation of the four models using Cohen's kappa coefficient (κ). The strength of agreement is interpreted according to the κ as κ: ≤ 0.20 = poor, 0.21-0.40 = fair, 0.41-0.60 = moderate, 0.61-0.80 = good and 0.81-1.00 = very good.[14-16] We studied 169 patients, 130 (81.1%) of whom were female, with a mean age of 65 ± 6.9 years. On the predictions, the proportions of high-risk individuals were 36.7% with the FRS cholesterol-based model, 47.3% with the FRS BMI-based model, 9.5% with the WHO/ISH cholesterol-based charts and 10.7% with the WHO/

ISH BMI-based charts. The agreement in stratifying patients into high and low-risk groups between the two versions of the FRS models (κ=0.736, p<0.0001) and the two versions of the WHO/ISH charts (κ= 0.804, p<0.0001) was "good". However, FRS were higher than that of the WHO/ISH charts, and the agreement between models was not satisfactory (between cholesterol-based models; FRS vs WHO/ ISH (κ=0.306, p<0.0001) and between BMI-based models; FRS vs WHO/ISH (κ=0.234, p<0.0001)). We concluded that FRS overestimated Sri Lankans' CV risk compared to the WHO/ISH charts. We published our findings in the *International Journal of Clinical Practice.*[17]

Research question 2

Next, we validated the 2007 WHO/ISH risk charts meant for the South East Asia Region – B (SEAR-B) in a Sri Lankan cohort, the Ragama Health Study (RHS).

RHS is a prospective, community-based cohort study established in 2007 in Ragama Medical Officer of Health (MOH) to obtain data on the prevalence of NCDs and risk factors. Ethics approval for this study has been obtained from the ERC of the Faculty of Medicine, University of Kelaniya (P/38/09/2006). The Ragama MOH area in 2007 had a multi-ethnic population of 75,591 people, with 15,137 housing units spread over an area of 25 km^2. This is an ongoing study conducted in adults aged 35-64 years selected by stratified random sampling in 2007. All patients have had anthropometry; two blood pressure (BP) measurements, and a venous blood sample taken for fasting blood sugar (FBS) and lipid profile at baseline. The participants are followed up at regular intervals to ascertain data on the development of new CVD (fatal CVD, non-fatal stroke, non-fatal myocardial infarction, coronary artery bypass graft (CABG) or percutaneous coronary intervention (PCI) in symptomatic individuals).

We extracted data on patients aged 40 or older in 2007 who had complete data on the 10-year CV outcome by 2017. We compared all observed incident CV events (i.e., first-ever CVD in the lifetime) from 2007 to 2017 with the predictions at baseline in 2007.

The initial RHS cohort consisted of 2923, of whom 2685 were followed for 10 years. We selected participants aged 40 or older at baseline with complete data to calculate CV risk predictions using WHO/ISH charts (N=2517) for our analysis. The cohort has had 215 incident CVDs (142 non-fatal and 73 fatal) over the 10-year follow-up. According to the predictions, 9.4% were at high risk in 2007, and 8.6% experienced incident CVD over 10 years of follow-up, indicating good overall prediction.

However, when studied in detail, we observed that the predictions were accurate in men and low-risk individuals but were less predictive in women, especially at high risk for CVD. We also observed that the predictions were more accurate when patients were divided into only two risk categories, i.e., low (<20%) and high risk (≥20%), rather than divided into several risk categories (Table 1). Furthermore, we observed that the predictions of both versions of the WHO/ISH charts, cholesterol-based and BMI-based, agreed with 81% of the cohort (κ=0.429; p<0.001). We concluded that

1. WHO/ISH (SEAR B) risk charts predicted the future CVD risk of males and low-risk females accurately.
2. Both versions of WHO/ISH (SEAR B) risk charts (cholesterol-based or BMI-based) could be used for risk stratification of Sri Lankans, depending on the availability of laboratory facilities.
3. Predictions were more accurate when stratifying subjects only into two groups: low-risk (<20%) and high-risk (≥20%).

We presented our findings at the 53rd Annual Academic Sessions of the Ceylon College of Physicians in November 2020 and won the E. M. Wijerama Award for the best presentation. We published our results in *PLOS One* in 2021.[18] This paper won the "Best publication by a Physician" award by the Ceylon College of Physicians in 2022 and the "Best publication by a Physician" award by the Sri Lanka College of Internal Medicine in 2022.

Combining all these findings, I wrote a review article for the *Journal of the Ceylon College of Physicians,* 2022.[19]

Research question 3

Even though WHO risk charts are satisfactory in predicting low-risk individuals, they are less sensitive to high-risk females. Therefore, we sought to develop a better model to predict the CV risk of Sri Lankans. We explored the feasibility of predicting CV risk using artificial intelligence. Ethics approval for this study was obtained from the ERC of the Faculty of Medicine, University of Kelaniya (P/61/09/2020). We conducted this project in collaboration with the Sri Lanka Institute of Information Technology, Malabe (SLIIT), as part of an MSc in Information Technology degree project. Of the RHS database, we selected data from 2596 patients,

Table 1. Validation of WHO/ISH (SEAR B) risk prediction charts* in Sri Lankans

10-year CV risk prediction (WHOASH charts with cholesterol)	*Male*		*Female*		*Total*	
	n	Observed CV events N (%) -18	n	Observed CV events N (%) -19	n	Observed CV events N (%) -20
<10%	987	94 (9.5) [8.6-10.5%]	1045	48 (4.6) [3.9-5.2%]	2032	142 (7.0) [6.4-7.6%]
10-19%	73	19 (26.0) [20.9-31.2]	177	12 (6.8) [4.9-8.7%]	250	31 (12.4) [10.3-14.5%]
20-29%	41	6 (14.6) [9.1-20.2%]	55	6(10.9) [6.7-15.1]	96	12 (12.5) [9.1-15.9%]
30-39%	14	4 (28.6) [16.5-40.6%]	48	8 (16.7) [11.3-22.0%]	62	12 (19.4) [14.3-24.4%]
≥40%	17	7 (41.2) [29.2-53.1%]	60	11 (18.3) [13.3-12.3%]	77	18 (23.4) [18.6-28.2%]
<20%	1060	113 (10.6) [9.7-11.6%]	1222	60 (4.9) [4.3-5.5%]	2282	173 (7.6) [7.0-8.1%]
≥20%	72	17 (23.6) [18.6-28.6%]	163	25 (15.3) [12.5-18.2%]	235	42 (17.9) [15.4-20.4%]

WHO/ISH – World Health Organisation and International Society of Hypertension, SEAR B Southeast Asia Region – B, CV – cardiovascular

40 years or above, naïve for CVD at baseline in 2007. Of them, 179 have developed incident CVDs over the 10-year period from 2007 to 2017. We used machine learning (ML) to analyse follow-up data and develop new predictive models. We developed ML-based models using the Google Colab ML platform with the Scikit-learn library in the Python programming language and the Train-Test Split method by dividing (9,10) participants' data into two groups: the training and testing samples.

We trained ML-based models on the training sample and tested them on the test sample. We trialled six standard ML classification algorithms with different modelling approaches, namely, Decision tree, Random Forest, k-nearest neighbour, 2D neural networks, AdaBoost and gradient boosting. We selected the model with the highest area under the receiver operating characteristic curves (AUC ROC) as the best model. We developed two models: the first one based on all available variables (75 variables), and the second one based on six conventional CV risk factors that are used in the WHO risk charts (e.g., age, sex, smoking status, systolic blood pressure, history of diabetes, and total cholesterol level). We compared the predictions of the new models with those of the WHO risk charts (SEAR, 2019) using the AUC-ROC. We observed that both the 75-variable model and the 6-variable model were more predictive than the WHO risk charts, with higher AUCs of 0.74 and 0.72 vs 0.55, respectively. Of the 179 incident CVDs recorded over the 10-year follow-up, 75- and 6-variable models correctly predicted 124 and 124 cases, but only 45 cases were predicted by the WHO risk charts (Figure 1). However, the prediction of low-risk individuals was almost similar with all three models, with 75- and 6-variable models and the WHO risk charts correctly

predicting 2293, 2293 and 2372, respectively. We concluded that the machine learning of follow-up data of Sri Lankans could improve CV risk prediction compared to using WHO risk charts, especially for high-risk individuals. We presented these findings at the 56th Annual Academic Sessions of the Ceylon College of Physicians in September 2023 and won the E M Wijerama award for the best presentation. We published our findings in the *Journal of Desk Research Review and Analysis* in 2024.[20]

We externally validated our 6-variable ML-model in a separate hospital-based validation cohort. This cohort consisted of 357 consecutive patients, 40-74 years of age, admitted to Colombo North Teaching Hospital from 1st of January 2019 to 1st of August 2020, who presented with an acute incident myocardial infarction or stroke (N=118) or a disease other than an acute CVD (N=239), who had complete data for CV risk calculation. The cohort's mean age was 63.4 (SD: 7.2) years, and 117 (32.7%) were male. We calculated their CV risk predictions at the time of hospital admission using both the 6-variable ML-model and the 2019 WHO risk charts separately. The 6-variable ML-model predicted 83/118 incident events, while the WHO risk charts could correctly predict only 28/118 events, giving positive predictive values of 87.3% and 35.8%, respectively (Figure 2). The ML-model predicted 310/357 cases correctly compared to 217/357 cases by the WHO risk charts. Therefore, we concluded that the 6-variable ML-based model derived from machine learning a cohort of Sri Lankans improved the overall accuracy of CV-risk prediction compared to the WHO risk charts in Sri Lankans. We published our findings in *BMJ Open*.[21]

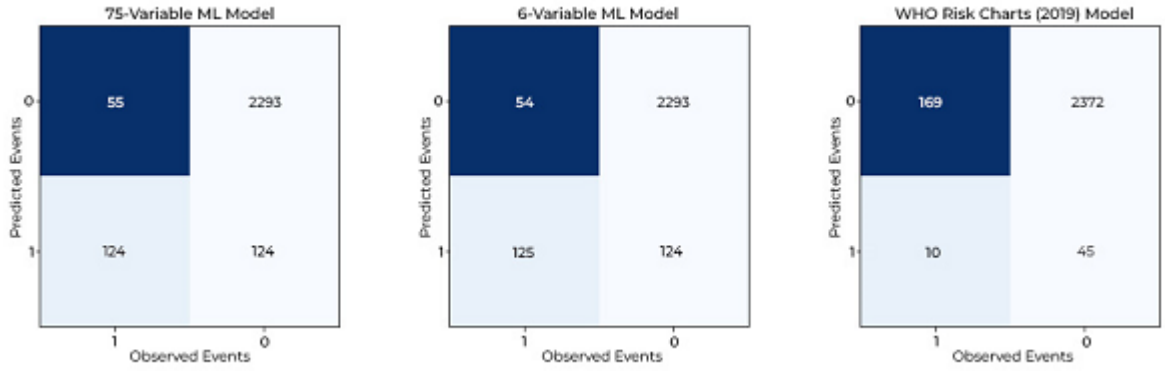

Figure 1. Comparison of the predictive performance of machine learning-based models and the World Health Organisation cardiovascular risk charts (Southeast Asia Region – 2019) in a Sri Lankan cohort.

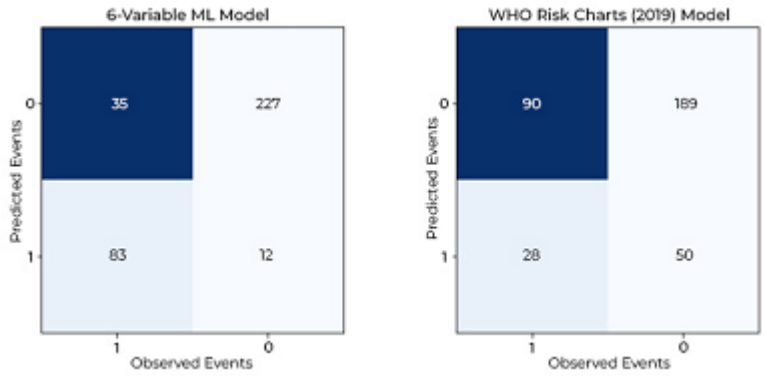

Figure 2. External validation of the 6-variable machine learning model in cardiovascular risk prediction.

Research question 4

The ultimate aim of CV risk prediction is to help detect the CV risk of patients efficiently. To achieve this goal, we need a reliable, user-friendly risk prediction model that is freely available from anywhere, especially at the periphery. Therefore, we finally developed a simple risk prediction model with a web-based interface for calculating Sri Lankans' CV risk. We used the same data as the RHS cohort. We identified the best predictive variables using feature importance and domain knowledge. We trialled several machine learning models using the variables according to their feature importance. We tried to use fewer and freely available variables to maximise the clinical use of the prediction models to be practically useful in resource-poor areas. We developed three models with a team at SLIIT and compared predictive performances between models and the 2019 updated WHO risk charts using receiver operating characteristic curves (ROC). We selected the best model by comparing AUC ROC, mean F1 score, recall, precision, accuracy and also the practicality of the models in terms of the free availability of the variables used in the model (Figure 3). We named the best model for use in primary care as the "SLCVD score". Models 1, 2, 3 (SLCVD score) predicted 173, 162, 169, while the WHO risk charts predicted only 10 out of 179 observed CV events. The AUC ROCs were 0.98, 0.98, 0.98 and 0.52, respectively.

We externally validated the predictions of the SLCVD score in the hospital-based validation cohort. We compared the predictions using the SLCVD score and the WHO risk charts with observed events. The SLCVD score predicted 38 more cases than the WHO risk charts (Figure 4).

We then developed a web-based interface for score calculation, the "SLCVD score calculator," to enhance the practical usefulness of the score (Figure 5). This is the first and only CV risk prediction model specific to Sri Lankans. The calculator uses the same CV risk variables in the WHO risk charts: age, sex, smoking status, history of diabetes, systolic blood pressure, and total cholesterol level. It predicts the 10-year risk of developing a hard CVD, i.e., a stroke, myocardial infarction, peripheral vascular disease or aortic aneurysm, as a percentage. A percentage ≥20% is defined as high risk. We presented these findings at the 137th Anniversary International Medical Congress of the Sri Lanka Medical Association in 2024 and won the E M Wijerama Award for the best paper in 2024 and the Special Prize in Cardiology for the best paper in Cardiology 2024. We published our findings in *PLOS One* in 2024.[22] This paper was selected for the Pramod Ranatunga Research Award of the Sri Lanka College of Cardiologists Academic Sessions 2025.

Further, we fine-tuned the model and the calculator to make it more generalisable to Sri Lanka using the nationally representative data of the STEPwise approach to surveillance (STEPS) survey done in 2021.

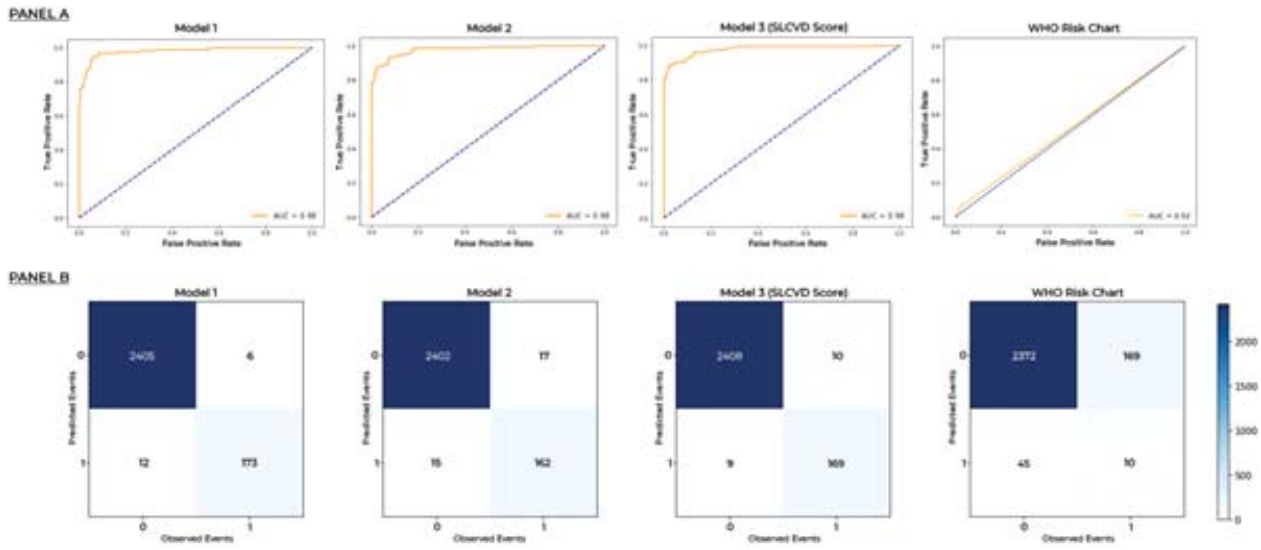

Figure 3. Comparison of different machine learning-based models.

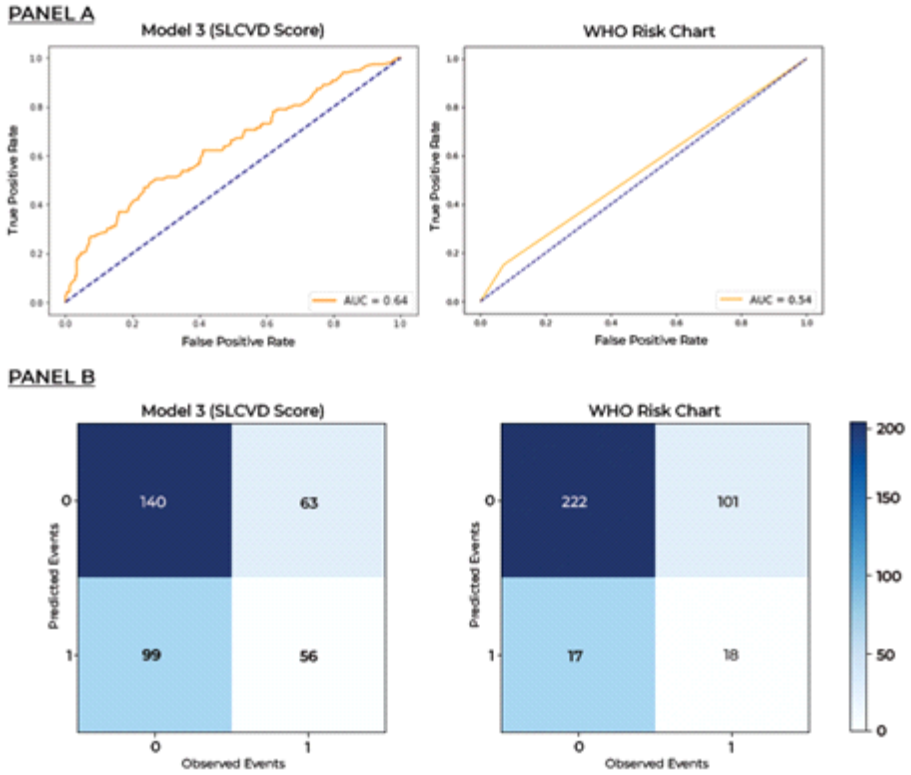

Figure 4. Comparison of cardiovascular risk predictions vs observed events using different prediction models in the external validation cohort

Panel A – Receiver operating characteristic curves

Panel B – Confusion matrices

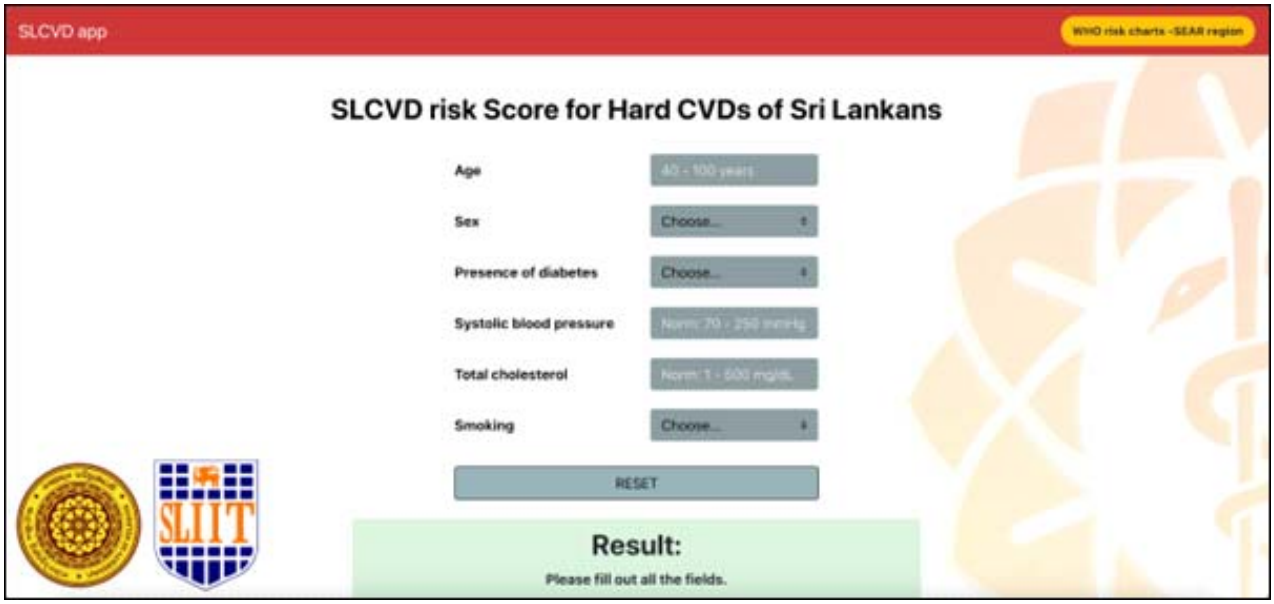

Figure 5. SLCVD score calculator.

Finally, we have submitted a patent application for this calculator to the National Intellectual Property Office of Sri Lanka, in accordance with the Intellectual Property Act, No. 36 of 2003. Upon securing the patent rights, we intend to launch the calculator through the Ministry of Health, making it freely and widely accessible for public use.

Conclusions and recommendations

Based on the results just presented, I have made the following conclusions and recommendations regarding CV risk prediction of Sri Lankans.

It is important to remember that CV risk predictions of Sri Lankans using different risk models are different. The 10-year CV risk predictions using the WHO/ISH risk charts do not agree adequately with the predictions of the FRS. The FRS overestimated the CV risk of Sri Lankans. Therefore, the same CV risk prediction model used at baseline should be used at follow-up in Sri Lankans, without interchanging risk prediction models.

Of the internationally accepted CV risk prediction models, the WHO (SEAR-2019) risk charts are the best for Sri Lankans. Both versions of the WHO risk charts, i.e., cholesterol-based and BMI-based, can be used to predict the CV risk of Sri Lankans, depending on the availability of data. It is important to note that the 10-year risk predictions of the WHO risk charts are more accurate in males and low-risk individuals than they are in high-risk females.

The risk prediction models developed with artificial intelligence using data from Sri Lankan cohorts are better than the WHO risk charts in the risk prediction of Sri Lankans. Of those, the SLCVD score calculator is the only CV risk prediction model available specifically to Sri Lankans. It predicts the CV risk of Sri Lankans, using age, sex, smoking status, history of diabetes, systolic blood pressure and total cholesterol level.

In conclusion, this oration has highlighted several key issues related to the CV risk prediction of Sri Lankans. I sincerely hope these recommendations will enhance the practical application of CV-risk prediction in Sri Lankans and ultimately help reduce the noncommunicable disease burden in Sri Lanka.

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