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Original Article

Association of Framingham cardiovascular disease risk scores with 10-year risk of cardiovascular mortality: a retrospective cohort study in South India

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ABSTRACT

Background: Few cohort studies examine the association of cardiovascular risk scores with cardiovascular mortality in India. This study assessed the association of baseline Framingham Risk Scores (FRS) with 10-year incidence of fatal CVD events in rural Tamil Nadu, India.

Methods: Using a retrospective cohort study design, we analysed the association of baseline FRS categories assessed in 2011-12 through a STEPS risk factor survey, with CVD deaths over 10 years. Causes of death for the survey participants aged 30–64 years at baseline (2011–12), were obtained through established vital event surveillance, while baseline FRS CVD scores were calculated using original and published recalibration equations.

Results: 3418 participants (1480 males, 1938 females), free of CVD at baseline, were followed up for mortality for 10.22 years (median). The CVD mortality rate was 3.01 per 1000 person-years among males and 1.36 in females. Those with baseline original lipid-based FRS ≥20 % had higher CVD mortality risk (Hazard Ratio males: 11.18, 95 % CI: 4.67–26.79; females: 17.51, 95 % CI: 6.07–50.55) compared to those with scores <10 %, with similar results using recalibrated scores. Discrimination statistics (Harrell's C) were 0.755 and 0.751 for original and recalibrated lipid-based scores in males, compared to 0.734 and 0.842 in females.

Conclusions: FRS had good predictive validity for cardiovascular mortality in a rural Indian population, confirming its clinical usefulness.

List of abbreviations

Abbreviation	Explanation
AHA/ACC	American Heart Association/American College of Cardiology
AIC	Akaike Information Criterion
BMI	Body Mass Index
CHD	Coronary Heart Disease
CI	Confidence Interval
CVD	Cardiovascular Diseases
FRS	Framingham Risk Score
GBD	Global Burden of Disease
HDL	High Density Lipoprotein
HIS	Health Information System
HR	Hazard Ratio
ICD	International Classification of Diseases
PROCAM	Prospective Cardiovascular Munster
PURE	Prospective urban and rural epidemiological study
QRISK	QRESEARCH cardiovascular risk algorithm
SCORE	Systematic COronary Risk Evaluation
SD	Standard Deviation
STEPS	STEPwise approach to NCD risk factor surveillance
VA	Verbal Autopsy
WHO/ISH	World Health Organisation/International Society of Hypertension

1. Introduction

The global prevalence of cardiovascular diseases (CVDs) such as coronary heart disease (CHD), stroke, and peripheral vascular disease

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has doubled over 30 years (from 271 million in 1990 to 523 million in 2019).[1] In India, during the same period, the death rate due to CVD rose from 140.5 to 185.1 deaths per 1,00,000 population.[2] The escalating burden of CVD, especially in the most productive ages, has led to an increase in catastrophic health expenditure. This calls for an urgent necessity for early diagnosis and treatment of CVDs in India.[3]

Risk factors are vital for predicting future cardiovascular events, either individually or as composite scores.[4,5] The approach of using algorithms based on risk factors for assessing CVD risk originated from the Framingham cohort and remains widely employed even today.[6] While the European Systematic Coronary Risk Evaluation (SCORE)[7] predicts only cardiovascular deaths (SCORE), other scores such as the FRS (Framingham Risk Score)- CVD, QRISK (QRESEARCH cardiovascular risk algorithm),[8] World Health Organisation/International Society of Hypertension (WHO/ISH) risk prediction chart,[9] and the Prospective Cardiovascular Munster (PROCAM) model,[10] predict total CVD events, including non-fatal cardiovascular events such as CHD, cerebrovascular events, as well as deaths. These risk scores can also be used to assess the need for and usefulness of preventive drug therapy.[11]

Cardiovascular risk factors identified by the Framingham Heart Study[12] include major non-modifiable (age, male gender, heredity, race), modifiable (tobacco smoking, high blood cholesterol, high blood pressure, physical inactivity, obesity/overweight, diabetes), and contributing risk factors (stress, alcohol, diet, and nutrition).[13] Studies from India have shown that FRS-CVD was a more effective risk assessment tool for identifying high-risk individuals, compared to other risk scores like the American Heart Association/American College of Cardiology (AHA/ACC) and QRISK, despite a low representation of persons of Indian ethnicity in the original Framingham study.[14,15] However, it was also found that FRS-CVD tends to underestimate CVD event risk, and calibration for Indian settings may be required.[16,17] Validation of FRS scores in predicting CVD events from Malaysia[18,19] found moderate to good discrimination and calibration. At the same time, a study from Germany used both original and recalibrated 30-year Framingham risk scores and showed adequate discrimination and calibration.[20] India lacks long-term, statistically powered cohort studies reporting the effect of predictors on the long-term risk of CVD events. Two previous cohort studies from India reported predictors of 10-year risk of CVD events, but had limitations such as using self-reported diabetes as a predictor[21] or had follow-up below five years (PURE, prospective urban and rural epidemiological study).[22]

In this study, we report the association of original and recalibrated lipid and body mass index (BMI)-based FRS-CVD scores with 10-year risk of CVD deaths, among a cohort of rural adults in Tamil Nadu, south India.[23]

2. Materials and methods

2.1. Study design, setting, and participants

A 10-year follow-up retrospective cohort study was conducted in 2021-22 among participants of a baseline WHO STEPwise approach to NCD risk factor surveillance (STEPS) survey conducted between April 2011 and December 2012, among 3799 rural adults aged 30–64 years in Vellore district. These individuals were from nine randomly selected villages from a rural community development block, which has been under long-term demographic surveillance by the institution implementing the study.[23] Those who were free from known CVD at baseline (based on a history of stroke, myocardial infarction, angina, and heart failure) were followed up for mortality from the date of participation in the survey in 2011-12 up to January 2022.

2.2. Calculation of baseline FRS-CVD scores and component variables

Although the detailed baseline survey methodology has been reported previously[23] in this article, we again clarify the variables used to calculate FRS-CVD scores and their measurement tools in brief. The variables used for calculating FRS-CVD scores included age, lipid values (including total cholesterol and high-density lipoproteins (HDL), systolic and diastolic blood pressure (mm Hg), and BMI as continuous variables, and smoking (based on the WHO STEPS questionnaire), diabetes (fasting plasma glucose $\geq$126 mg/dl or on treatment) and treatment status for raised blood pressure.[24] In our previous paper, we reported the percentage of survey participants in four different categories of FRS-CVD scores (<10 %, 10–19.9 %, 20–29.9 %, $\geq$30 %).[24] The paper also explained how these scores were calculated using 1) the original equations published by D'Agostino et al[25] and 2) a recalibration process for the FRS-CVD scores using average risk factor levels for the same cohort. Our second paper presents the association of the baseline FRS risk categories with observed fatal CVD events over 10 years (2011–2022), and also assesses the performance of the FRS to predict the 10-year risk of CVD deaths.

2.3. Ascertainment of outcome

Data on mortality and migration were obtained from the routine demographic surveillance system, which is recorded in a computerised health information system (HIS), managed by a community medicine department of a medical college for over 30 years.[26] Vital event surveillance through primary care workers captured causes of death, recorded using hospital records or verbal autopsies (VA), adjudicated by a physician if hospital records were not available.[26] Causes of death were categorised based on International Classification of Diseases-9 (ICD-9) codes, to identify cardiovascular deaths (410-acute myocardial infarction, 411-other acute and subacute forms of ischemic heart disease, 428-heart failure, and 436-acute but ill-defined, cerebrovascular disease).[27] The cohort dataset was created by merging the HIS data on mortality and migration with the baseline survey data collected in 2011–12.

2.4. Statistical analysis

Continuous variables are presented as means and standard deviations (SD), whereas categorical variables are presented as counts and percentages. Age-specific all-cause and CVD-specific mortality were calculated as rates per 1000 person-years. Person time for each participant was calculated as the time from the date of the baseline survey to the date of death, lost to follow-up due to migration, non-CVD related death, or the end date of the follow-up study (January 31st, 2022). Age-standardised mortality rates were calculated using the WHO world standard population.[28] Age-specific risk ratios for 10-year mortality were estimated using Poisson regression.

In the absence of data on non-fatal CVD events, we chose CVD mortality as the outcome measure of interest. We used the complete data set without division into development and validation datasets, given the small number of events (69 CVD deaths).[24] Sex-specific survival probability at different time points was estimated using Kaplan–Meier survival curves,[29] and survival times of participants in different FRS risk categories (<10 %, 10–19.99 %, and $\geq$20 %)[11] were compared using the log-rank test.

We used two different models to estimate the association of time to death due to CVD, with lipid-based and BMI-based Framingham heart study risk scores. Sex-specific Cox proportional hazards regression with non-informative censoring was done to estimate the association of baseline FRS-CVD with cardiovascular mortality, using hazard ratios (HR) and 95 % confidence intervals (CI). Time to event was defined as the time to death due to CVD, death due to other causes, migration, or the end of the study, whichever came first. Proportional hazard assumptions were checked using scaled Schoenfeld residuals both graphically and statistically, after fitting the model. The fit of the models was assessed using Akaike information criterion (AIC) values.[30]

As an additional analysis, deaths from non-CVD causes that act as competing risks[31] were handled separately in a competing risks model. Fine and Gray sub-distribution hazard model[32] was used to develop the competing risk model. We preferred the Fine and Gray sub-distribution hazard model over the cause-specific hazard model as our primary interest was predicting risk rather than elucidating aetiology.

Discrimination of FRS-CVD (original and recalibrated, for both lipid and BMI-based scores) in predicting cardiovascular mortality was assessed using Harrell's C statistics.[33] The overall fit of the model was assessed using a plot of cumulative hazard (Nelson-Aalen) against Cox-Snell residuals, using the *estat gofplot* command in STATA version 18.0. Additionally, we also assessed the agreement between the original lipid-based FRS CVD risk score categories and the BMI-based FRS CVD risk score categories using weighted and unweighted Cohen's Kappa statistics.

We calculated 95 % CIs for the estimates, and a *P*-value <0.05 was considered statistically significant. Data were analysed using STATA version 18.0 (Stata Corp LLC, Texas USA) and R studio (RV4.1.0, packages: AER, epitools, tableone, cmprsk, vcd). Data visualisation was done using packages (ggplot2, survival, survminer) available in R Studio (RV4.1.0).

3. Results

Out of 3799 survey participants, 3418 (89.97 %) with no known history of CVD at baseline (Fig. 1) formed the cohort for the current study, of which 1480 (43.30 %) were male and 1938 (56.70 %) were female. The mean (SD) years of education were 7.72 (4.30) for males, and 4.17 (4.46) for females. While 30.12 % of males were agricultural workers, 45.63 % of females were housewives or unemployed. A total of 43 cohort participants (1.26 %) migrated out of the study area after contributing 151.67 person-years of follow-up. Baseline risk factor data to calculate BMI-based FRS-CVD were available for 89.76 % (3068) of the 3418 participants, while data to calculate lipid-based scores were available for 89.55 % (3061). The baseline values of FRS risk factors for this cohort who were all participants without known CVD at baseline, are shown in Supplementary Table 2. The overall prevalence of diabetes at baseline was 10.89 % (335/3,077, with 341 missing values), with 11.88 % prevalence in males and 10.15 % in females (Supplementary Table 2).

There were 230 deaths over the median follow-up period of 10.22 years (33,446.52 person-years). The overall all-cause mortality rate was 6.88 per 1000 person-years (males: 10.15 per 1000 person-years, females: 4.44 per 1000 person-years). The proportionate mortality rate due to CVD was 30.0 % (69/230) (Fig. 1). The CVD-specific mortality rate was 2.06 deaths per 1000 person-years (males: 3.01 per 1000 person-years, females: 1.36 deaths per 1000 person-years) (Supplementary Table 1). Age-standardised all-cause and CVD-specific mortality rates were 9.32 and 2.70 per 1000 males and 4.33 and 1.32 per 1000 among females, respectively.

3.1. Cox regression model

Those with higher FRS-CVD scores (categories 10–19.99 % and ≥20 %) at baseline, had significantly lower survival compared to those in the lowest risk category (<10 %), as seen in the Kaplan–Meier curves (log-rank test *P*-value <0.0001), using both original and recalibrated FRS-CVD scores (Fig. 2a and b).

Among males, those in the highest baseline risk category according to original lipid-based FRS-CVD (score ≥20 %) had 11.18 times higher CVD mortality (HR 95 % CI: 4.67–26.79) compared to those with baseline scores of <10 % (Table 1a). Similar hazard ratios were obtained with recalibrated lipid-based scores (HR: 12.72; 95 % CI: 4.38–36.92). Similarly, those with a baseline BMI-based FRS-CVD ≥20 % had a 13.29 times higher risk of dying when compared to those with scores <10 % (HR 95 % CI: 5.85–30.19). Those with high recalibrated BMI-based scores (≥20 %) had 10.58 (95 % CI: 4.34–25.78) times higher CVD mortality in 10 years compared to those at lowest risk (Table 1a).

Among females, those with baseline lipid-based FRS-CVD ≥20 % had 17.51 (95 % CI: 6.07–50.55) times higher risk of CVD mortality within 10 years than those with baseline scores of <10 % (Table 1b). Females with original BMI-based FRS-CVD risk scores ≥20 % had a very high risk of CVD deaths (HR: 30.63; 95 % CI: 10.24–91.64) compared to those with scores <10 %. When using the recalibrated scores, these HR values for the highest baseline category (≥20 %) were slightly lower: HR for lipid-based FRS-CVD: 21.95 (95 % CI: 7.35–65.55); HR for BMI-based score: 18.99 (95 % CI: 7.35–49.03).

The Cox proportionality assumptions were fulfilled by all the models except for the recalibrated lipid-based FRS-CVD model among females

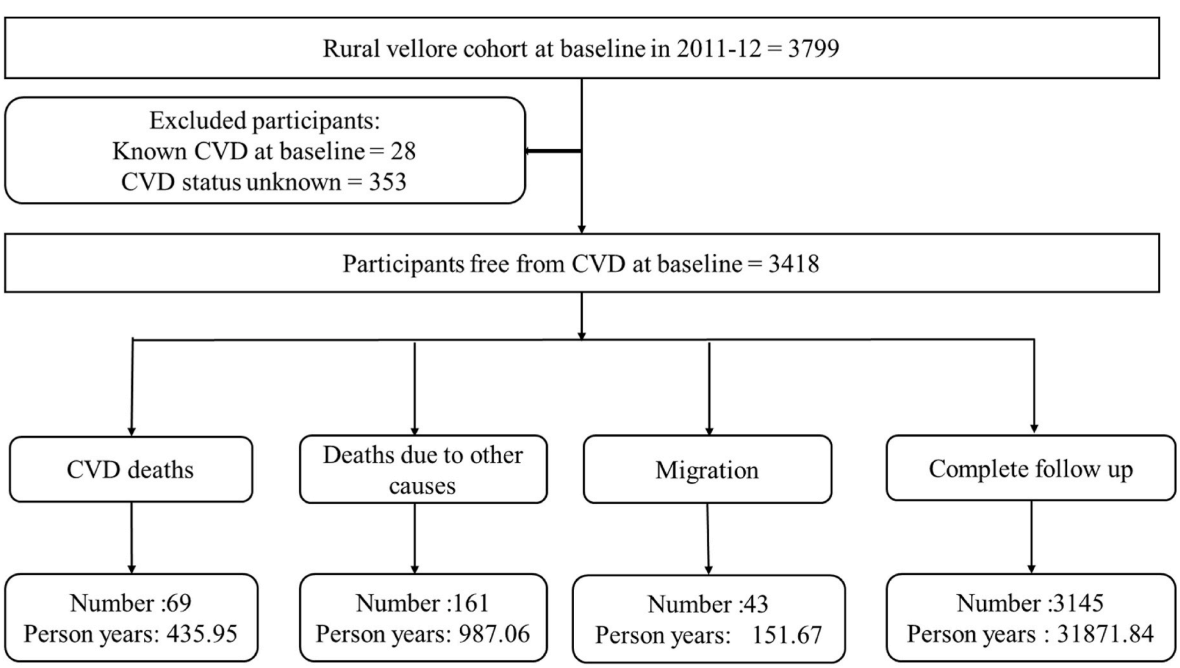

Fig. 1. Flow diagram for the follow-up of the Vellore rural cohort.

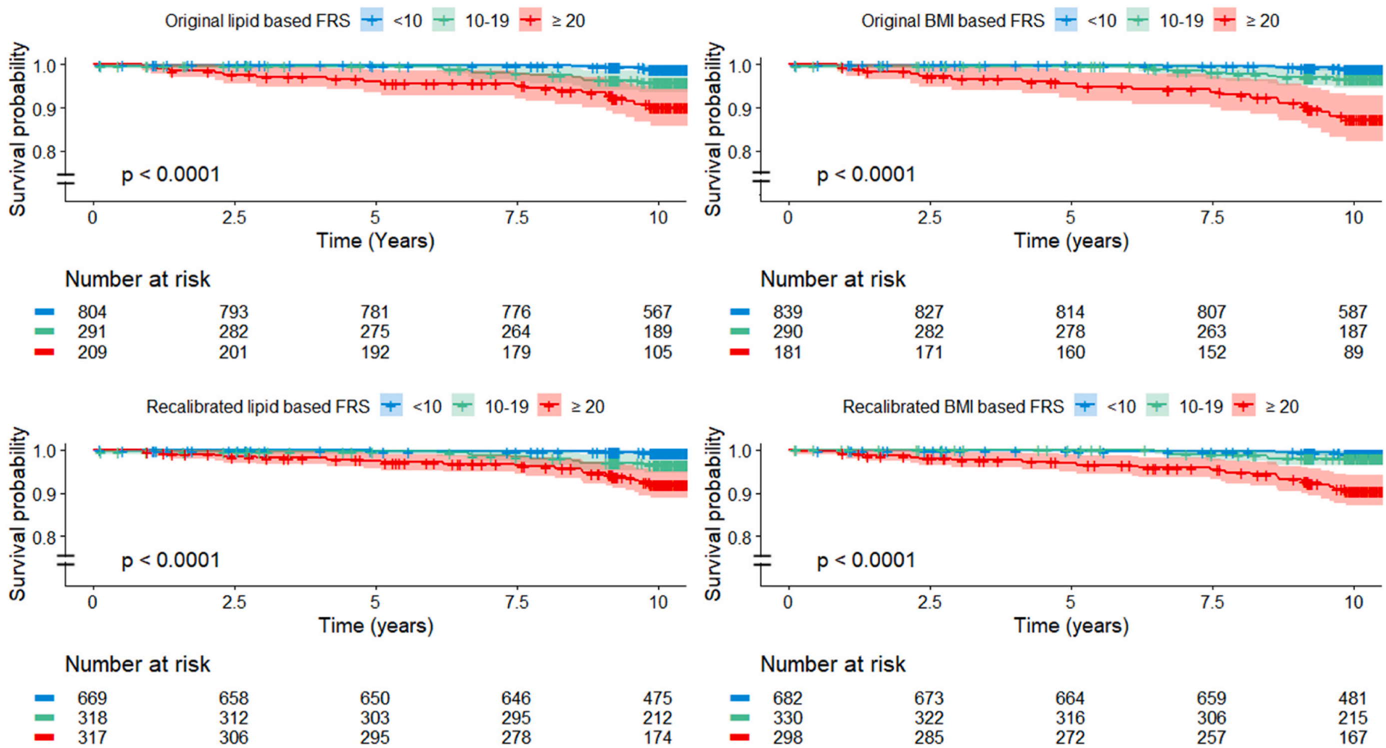

Fig. 2a. Kaplan–Meier curves comparing CVD-free survival according to FRS categories among males.

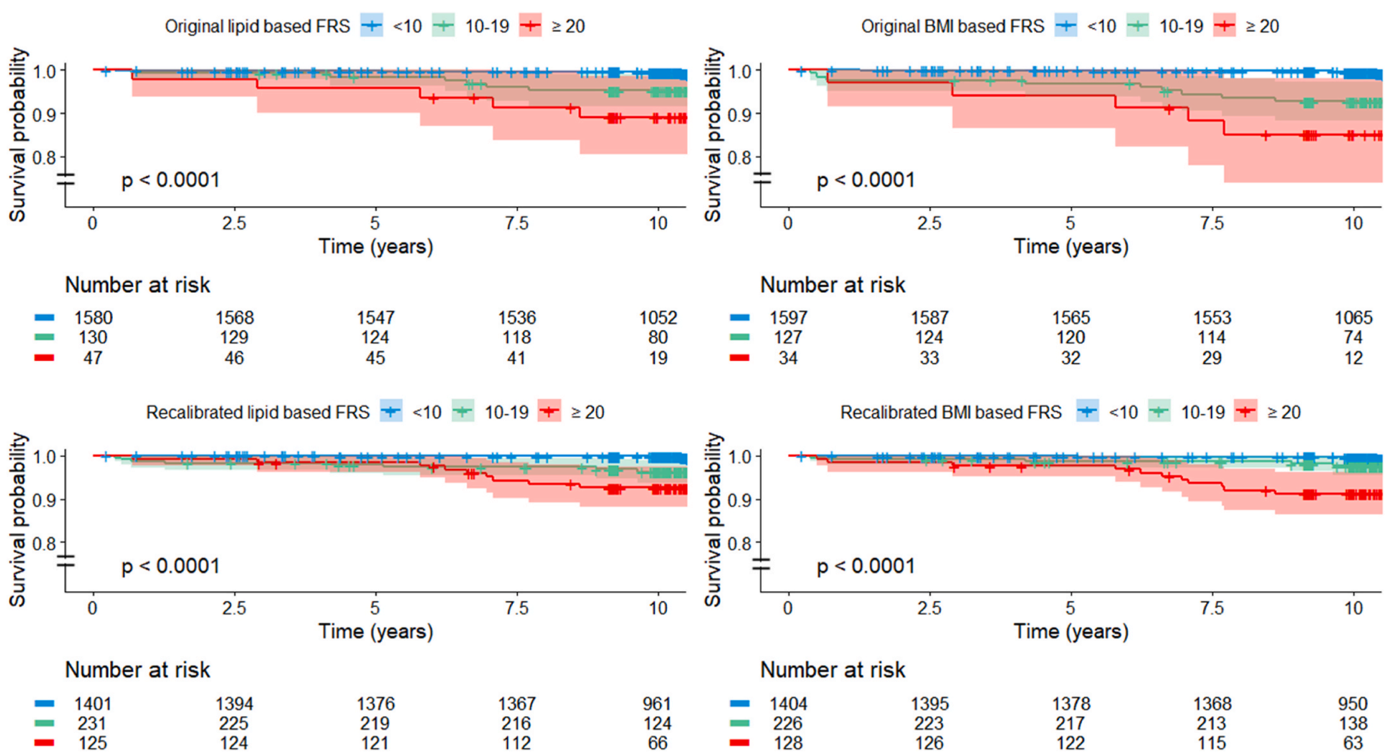

Fig. 2b. Kaplan Meier curves comparing CVD-free survival according to FRS categories among females.

(*P*-value = 0.02) (Supplementary Fig. 1a, Supplementary Fig. 1b, and Supplementary Table 3).

The model fit assessed using AIC values showed similar values for both original and recalibrated models using both lipid-based and BMI-based FRS scores among males (Table 2). In general, the original models had a better AIC than the recalibrated, but these differences were minimal, except in the lipid-based model for females, where the recalibrated score (287.80) had a better AIC value compared to the original (299.50) (Table 2).

The C statistics were only slightly better (higher) for the corresponding recalibrated models when compared to the original models among females (Table 2). BMI-based FRS-CVD showed better

Table 1a
Association of baseline FRS-CVD risk scores with 10-year CVD mortality among males.

Category of risk score (%)	CVD deaths* (n)	Person-years of follow-up [a]	Mortality rate per 1000 person-years	Hazard ratio (Cox proportional hazards) (95 % CI)	P-value	Subdistribution hazard ratio for CVD mortality (95 % CI)	P-value
Original lipid-based FRS-CVD score							
<10	7	7975.68	0.88	Ref	Ref	Ref	Ref
10–19.99	11	2776.93	3.96	4.59 (1.78–11.85)	0.002	4.43 (1.72–11.42)	0.002
≥20	18	1909.77	9.42	11.18 (4.67–26.79)	<0.001	10.55 (4.42–25.19)	<0.001
Recalibrated lipid-based FRS-CVD score							
<10	4	6628.1	0.60	Ref	Ref	Ref	Ref
10–19.99	10	3085.58	3.24	5.44 (1.71–17.36)	0.004	5.36 (1.68–17.07)	0.005
≥20	22	2948.72	7.46	12.72 (4.38–36.92)	<0.001	12.05 (4.16–34.95)	<0.001
Original BMI-based FRS-CVD score							
<10	8	8298.01	0.96	Ref	Ref	Ref	Ref
10–19.99	9	2786.15	3.23	3.40 (1.31–8.80)	0.012	3.30 (1.28–8.56)	0.014
≥20	20	1620.16	12.34	13.29 (5.85–30.19)	<0.001	12.37 (5.46–28.02)	<0.001
Recalibrated BMI-based FRS-CVD score							
<10	6	6767.62	0.89	Ref	Ref	Ref	Ref
10–19.99	6	3195.25	1.88	2.14 (0.69–6.63)	0.189	2.10 (0.68–6.51)	0.199
≥20	25	2741.44	9.12	10.58 (4.34–25.78)	<0.001	9.95 (4.09–24.19)	<0.001

[a] For 1304 participants for whom lipid-based FRS-CVD scores were available and 1310 with BMI-based FRS-CVD scores.

Table 1b
Association of baseline FRS risk scores and 10-year CVD mortality among females.

Category of risk score (%)	CVD deaths (n)	Person-years of follow-up [a]	Mortality rate per 1000 person-years	Hazard ratio (Cox proportional hazards) (95 % CI)	P-value	Subdistribution hazard model for CVD mortality (95 % CI)	P-value
Original lipid-based FRS-CVD score							
<10	11	15696.77	0.70	Ref	Ref	Ref	Ref
10–19.99	6	1246.98	4.81	6.95 (2.57–18.79)	<0.001	6.91 (2.56–18.68)	<0.001
≥20	5	432.01	11.57	17.51 (6.07–50.55)	<0.001	16.98 (5.98–48.21)	<0.001
Recalibrated lipid-based FRS-CVD score							
<10	5	13992.73	0.36	Ref	Ref	Ref	Ref
10–19.99	8	2200.40	3.64	10.73 (3.50–32.85)	<0.001	10.51 (3.54–31.20)	<0.001
≥20	9	1182.64	7.61	21.95 (7.35–65.55)	<0.001	21.50 (7.32–63.14)	<0.001
Original BMI-based FRS-CVD score							
<10	9	15878.34	0.57	Ref	Ref	Ref	Ref
10–19.99	9	1199.72	7.50	13.49 (5.35–33.99)	<0.001	13.33 (5.32–33.41)	<0.001
≥20	5	305.38	16.37	30.63 (10.24–91.64)	<0.001	29.42 (10.0–86.58)	<0.001
Recalibrated BMI- based FRS-CVD score							
<10	7	13995.68	0.50	Ref	Ref	Ref	Ref
10–19.99	5	2187.21	2.29	4.70 (1.49–14.82)	0.008	4.62 (1.48–14.41)	<0.001
≥20	11	1200.55	9.16	18.99 (7.35–49.03)	<0.001	18.64 (7.34–47.39)	<0.001

[a] For 1757 participants for whom lipid-based FRS-CVD scores were available and 1758 with BMI-based FRS-CVD scores.

Table 2
Discrimination statistics (Harrell's C) and Akaike Information Criterion (AIC) values for FRS-CVD scores in predicting 10-year CVD mortality.

	Male			Female		
	C statistics (SE)	Contrast[a] (SD)	AIC value	C statistics (SE)	Contrast[a] (SD)	AIC value
Lipid-based FRS-CVD score as a predictor						
Original FRS-CVD scores	0.755 (0.037)	−0.004 (0.019)	478.50	0.734 (0.055)	0.108 (0.04)	299.50
Recalibrated FRS-CVD scores	0.751 (0.034)		480.12	0.842 (0.038)		287.80
BMI-based FRS-CVD score as a predictor						
Original FRS-CVD scores	0.767 (0.039)	−0.009 (0.017)	484.99	0.798 (0.05)	0.009 (0.026)	298.23
Recalibrated FRS-CVD scores	0.758 (0.037)		489.66	0.807 (0.048)		304.95

[a] The difference in the C statistic values between the original and recalibrated models.

discrimination than lipid-based scores in predicting CVD mortality, as evidenced by higher C statistics (Table 2). The goodness of fit plot among males and females showed that they were aligned with the diagonal with few departures at the right end of the curve, indicating that all models fit well (Supplementary Fig. 2a and 2b). In the original FRS CVD risk score categories, we found substantial agreement between lipid-based and BMI-based score categories in both sexes (males: weighted Cohen's kappa = 0.855; females: weighted Cohen's kappa = 0.819). Similar values were obtained for the recalibrated lipid- and BMI-based FRS categories in both sexes, as shown in Supplementary Table 4.

3.2. Competing risk model

In both genders, the hazard ratios obtained from the Cox regression model were almost similar to those of the subdistribution hazard models. The subdistributional HRs were higher for females in the highest (≥20 %) baseline FRS-CVD category compared to those in the lowest (<10 % score) category, for both the original lipid-based model (females: 16.98, 95 % CI: 5.98–48.21, males: 10.55, 95 % CI: 4.42–25.19) and recalibrated models (females: 21.50, 95 % CI: 7.32–63.14, males: 12.05, 95 % CI: 4.16–34.95) (Tables 1a and 1b). A similar pattern of larger HR values in females was seen with BMI-based FRS-CVD (Tables 1a and 1b).

4. Discussion

Our study found strong, statistically significant associations between the high-risk category of FRS, both original and recalibrated, with 10-year CVD mortality, using either BMI-based or lipid-based scoring systems.

We also observed that the recalibrated Framingham risk scores did not improve model fit or performance compared to the original ones, indicating that the original FRS-CVD was sufficient. A study that validated the 30-year Framingham risk score in the German population also found that original and recalibrated FRS discriminated CVD event-free survival equally,[20] while a study from China found that recalibrated risk scores predicted mortality slightly better than the original.[34] Other studies from Asia have also concluded that FRS can be used in most Asian populations, reporting good performance.[19,35]

Our study found that both lipid-based and BMI-based FRS-CVD scores had good discrimination values for predicting cardiovascular mortality. Given the higher ease of calculating BMI-based FRS-CVD in low-resource settings, compared to lipid-based scores and the good predictive validity for predicting CVD deaths in 10 years, the use of the simpler office-based BMI-based risk score could be a recommendation for primary care settings that do not have access to lipid testing. A study from Uganda also reported that the BMI-based FRS had good agreement with the lipid-based FRS (kappa 0.8)[36] which was similar to our study.

The overall mortality rate experienced in our CVD-free rural cohort aged 30–64 years at baseline was 6.88 per 1000 person-years, which was much lower than the 19.8 per 1000 person-years mortality rate reported from a study conducted in urban Chennai, Tamil Nadu, among adults aged 20 years.[37] This may be due to either rural-urban differences or differences in age distribution (inclusion of people >64 years), or inclusion of participants irrespective of baseline CVD status in the Chennai study, compared to our study, which followed younger adults (30–64 years) who were all free of CVD at baseline.[37]

The CVD-specific mortality rate was 2.06 per 1000 person-years in our study, similar to 2.9 per 1000 person-years reported from rural Tiruvallur, Tamil Nadu, which followed individuals aged 25–64 years for a median of seven years.[21] Similar rates were reported by the Global Burden of Disease (GBD) study in 2021, with an overall cardiovascular disease (CVD) mortality rate in India of 2.03 deaths per 1000 population.[38] Interestingly, a multi-site South Asian study (PURE sub-study),[39] which included rural and urban subjects from India, Bangladesh, and Pakistan, found that rural populations had higher CVD mortality compared to urban. This could not be assessed from our study due to a lack of mortality data for the urban component of our 2011-12 survey. The proportional mortality rate in our rural cohort aged 30–64 years was 30 %, while it was 24.46 % across all age groups in India in 2021, according to the GBD report.[38]

The main strengths of our study were the representative sample from a rural south Indian cohort, long follow-up, maximizing the availability of an existing DSS, using fasting plasma glucose at baseline to define diabetes for those not on treatment, and a good follow-up rate (only 1.3 % loss to follow-up due to migration).

To our knowledge, this is also the first study from South India that has accounted for competing risks in such an analysis and is one of the few long-term studies that provides ten-year CVD-specific mortality rates among adults residing in India based on baseline FRS CVD categories. We found similar hazard ratios using conventional Cox regression and Fine and Gray models, possibly due to the very low number of events of interest and the infrequent occurrence of competing events. However, a slightly higher hazard ratio was observed in the conventional Cox model, as many other studies have also reported.[40,41]

The study shows the value of meticulously recorded mortality data from an established demographic surveillance system (DSS) that has been functioning for more than 30 years. In the absence of research funding to convert the initial cross-sectional survey into a prospective cohort with tracking of both non-fatal and fatal events, we have attempted to link baseline risk levels to observed mortality based on a strong routine DSS.

The main limitations of this study were the inclusion of only one geographical area in rural south India, a relatively small number of CVD events in ten years, and the non-availability of data on non-fatal CVD events, which led to the inability to use FRS risk scores to predict total CVD events, with restriction to prediction of fatal CVD events.

5. Conclusions

The findings from this study confirm the usefulness of FRS CVD calculations in clinical practice for management decisions, such as the decision to prescribe statins, as those in the highest risk category (20 %) were at least 10 times more likely to die of CVDs in ten years. However, since the study was retrospective, we could not measure incident non-fatal CVD events or obtain data on behavioral changes such as changes in smoking status over the duration of the study. Further research is needed to assess the predictive validity of FRS CVD for predicting total CVD events using a prospective design, develop new risk equations using Indian cohorts, and possibly evaluate additional risk factors that are not part of the FRS equations.

Ethics approval

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board (IRB) of Christian Medical College Vellore, India (IRB Min—no 13954 (OBSERVE), dated 28.04.2021. The participants provided written informed consent at the time of baseline assessment.

Data availability

Data will be shared upon reasonable request to the corresponding author at midhun.s@cmcvellore.ac.in or with the senior author at anuoommen@cmcvellore.ac.in after manuscript publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ihj.2025.07.001.

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