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Association of Index of Cardiovascular risk factors with Socio-economic status index

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Abstract

Association between socioeconomic status (SES) with cardiovascular disease (CVD) and cardiovascular risk factors (CVRFs) have been observed empirically with contrasting results over genders and age-profiles. Better understanding of relationships between SES and CVRFs is critical in identifying optimal medical, social, and economic interventions to mitigate the burden of CHD, particularly among vulnerable groups. For a given time period, the paper describes age-specific and gender-specific index of cardiovascular risk factors (I_{CVD-RF_t}) and Index of socio-economic status (SES_t) for a region by normally distributed scores, avoiding limitations of ordinal/categorical scores facilitating parametric analysis for meaningful comparisons, classification, identification of critical areas and integration of various scales. Association between I_{CVD-RF_t} and SES_{AA} can be established by correlation, multivariate regression of the form $I_{CVD-RF_t} = \alpha + \sum \beta_i SES_{AA_{i_t}}$ or by canonical correlation analysis considering p-numbers of CVRFs and q-dimensional vector of SES, even if $p \neq q$. Empirical relationship can also be estimated between actual CVD prevalence or CVD death rate and the proposed indices I_{CVD-RF_t} and/or SES_t along with fluctuation of association across time. Relationship between SES and CVD-risks along with identification of critical areas helps to plan medical, social, and economic interventions to mitigate the burden of CHD. Professionals and researchers can take advantages of the proposed method including detection of changes by longitudinal data and better evaluating psychometric parameters from single administration

Keywords: Cardiovascular risks, Socioeconomic status, Normal distribution, Regression

Introduction

Relationships of health and socio-economic status (SES) have been investigated empirically and socio-economic inequalities have been given priority for public health in general and cardiovascular disease (CVD) in particular [1, 2]. SES is found to be inversely associated with CVD and CVD risk factors (CVRFs) and males are more sensitive to income and education than females regarding CVD mortality [3]. Low SES is linked with higher risk of developing premature Coronary heart disease (CHD) [4]. CVRFs influence the pathogenesis and development of CHD at different ages for different genders. CHD mortality in low-income counties exceeded the same for those with higher income [5]. Better understanding of relationships between SES and CVRFs is critical in identifying optimal medical, social, and economic interventions to mitigate the burden of CHD, particularly among vulnerable groups [6]. Yet the impact of SES factors such as income, education, and insurance status on the onset of premature CHD remains understudied [7].

As a moderator variable, SES affects direction and strength of the relationship with the predictor variable(Y) say CVD outcomes or CVD-risks. Thus, inferences about the moderating variable need significant statistical interactions with Y. An indicator of SES is a mediating variable explaining the process through which SES and Y are related. Common tools for assessment of CVD-risks are questionnaires covering risk factors such as age, gender, height and weight, family history, lifestyle habits like diet and exercise, and laboratory based factors like blood pressures (Systolic and Diastolic), cholesterol (total, HDL, LDL), body mass index (BMI); left ventricular hypertrophy (LVH); right ventricular hypertrophy(RVH); antihypertensives; diabetes mellitus (DM); triglycerides(TRG); etc. Results of such assessment tools

are compared with clinical data on CHD. A lower percentage implies less risk of the individual in developing heart disease in near future; higher percentage implies greater risk and immediate consultation with doctors who may recommend steps to lower the risk.

Different assessment tools differ with respect to the baseline risks, predictors, and outcomes [8]. CVD-risk tools do not work well in diversified populations and tend to overestimate or underestimate the risks [9]. CVD-risk models involving different population characteristics and performance variability are not standardized [10 – 11] and show limitations in temporal and spatial applicability. The models failed to explain changes in cardiovascular morbidity and mortality across time [12]. Geographical limitations associated with the models act as hindrance to universal applicability [13]. Many predictive models for CVD-risk in the general population have not undergone an external validation [14]. CVD- risk markers termed "new risk factors" like C-reactive protein (CRP), coronary calcium, interleukin-6 etc. are not yet considered by the CVD-risk models despite strong correlations observed between ultrasensitive CRP level and occurrence of acute coronary syndromes and cardiovascular deaths [15-16]. Need felt for improved CVD-risk tools covering all relevant variables which can be validated in various populations [17].

Multidimensional SES includes finite number of dimensions relating to a person/household within a community [18]. SES is recognized as a critical factor influencing access to resources and opportunities and contributing to health disparities [19]. However, comprehensive and valid composite SES for adults providing evidence-based interventions to mitigate health disparities are limited [20]. The issues of SES comparability among individuals with similar education level or income level have been raised along with effect of ignoring potentially important socioeconomic factors [21]. Limitations of three popular scales of SES used in Indian context were found [22]. Hence, there is a need to measure methodologically sound index of SES for the t-th time period (SES_t) for a region or country considering all the relevant dimensions.

For a given time period, the paper describes age-specific gender-specific index of CVD-risk factors(I_{CVD-RF_t}) by combining relevant CVD-risk factors and SES_t satisfying desired properties and facilitating meaningful association and undertaking statistical analysis across time and space.

Literature review:

Low SES groups showed higher prevalence of CVD-risk factors including those based on laboratory results [23] where diet was taken as a mediator and SES considered three dimensions: occupation (work prestige), education (social status) and income (economic status). However, the three chosen dimensions with significant overlaps may fail to present a comprehensive profile of SES which contains other different dimensions reflecting social position of an individual or a household. In addition, relative importance of the social factors and their relationships to health status is not known. Similarly, CVD-risk factors may go beyond obesity, hypertension, DM, hyper-cholesterolaemia etc. and ncludes lifestyle, diet habit, physical activity,

age, gender, diabetes, heredity, etc. [1]

Consideration of CVD-risk factors in non-exhaustive fashion and limited dimensions of SES in different studies gave different results. For example, [24] found higher SES is associated with more adverse CVD-risk profile where SES was based on household possessions, educational status and paternal education and CVD-risks were: BMI, waist circumference, blood pressure, glucose tolerance, plasma cholesterol and triglyceride levels, alcohol and tobacco consumption. Data on educational status, paternal education, household possession, etc. are often recorded under 4 to 5 categories. Summative scores assigning equal weight to the categories regardless of their values/utilities is a disadvantage. Cross-sectional studies measuring SES indicators and CVD-risk factors fail to comment on the temporal relationships between such factors. Collapsing of categories due to small numbers in the specific sub-categories may blur important differences.

Instead of individual traditional risk factors, composite CVD-risk factor profile covering amongst others traditional risk factors were preferred [25]. To assess CVD (predictor variable) [26] used the questionnaire where subjects give "Yes – No" answers to whether a doctor had been ever told that he/she had a (i) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems? (ii) high blood pressure or hypertension? (iii) stroke? Here, the questionnaire score (Y) is taken as sum of responses to the above said dichotomized questions and ranges from zero (no CVD history) to three and is not suitable for regressing Y on the SES-components as independent variables. CRF-scores based on six CVD-risk factors (hypertension, diabetes, hypercholesterolemia, smoking, obesity, and insufficient physical activity) was classified as "Poor" (3 - 6 risk factors), "Average" (1–2), or "Optimal" (0 risk factors) [27]. CRF-score were used to find association between CRF profile and CVD mortality by Kaplan Meier curves or Cox proportional hazards regression models.

However, such self-report data may not reflect the actual prevalence rates of CVD.

[17] indicated 18 CVD-risk estimation models starting from Framingham Heart Study (FHS) [28] to pooled cohort equation atherosclerotic cardiovascular disease ASCVD [29] with different sets of risk factors and limitations affecting their performance. Use of FHS is not recommended being obsolete [30]. All CVD-risk scales failed to account for the variable effects of different age groups [17]. CVD incidences differed among men and women primarily due to hormonal and physiologic differences. While PROCAM risk model by [31] underestimates CHD risk in women, the Reynolds Risk Score tended to overestimate CVD-risk for women [32]. Thus, age-specific and gender-specific measure of CVD-risks is preferred.

Obesity in CVD-risks is taken as BMI ≥30 kg/m^2[7]. BMIs are not additive and average BMI is misleading. One solution is to consider$\log(BMI) = \log(weight\ in\ kg) + 2\log(height\ in\ m)$. Insufficient physical activity is decided based on non-participation in moderate-intensity aerobic physical activity for >150 min/week, or vigorous-intensity aerobic physical activity for >75 min/week, or a total combination exceeding 150 minutes/week of moderate/vigorous-intensity aerobic physical activity. Identification of thresholds blood pressure and cholesterol for therapeutic measures is not uniform [33].

Major methodological limitations of SES scales:

- SES scales with different dimensions, number of items, item formats, are not comparable.
- May not cover all relevant dimensions and indicators. Narrow selection of variables may fail to represent the overall picture. Too many selections of variables are likely to increase multicolinearity, which inflate standard error in regression analysis.
- Poor measurements of indicators. For example, occupational prestige in the *Duncan Socioeconomic Index* is assessed in subjective fashion [34].
- Distribution of Items scores and summative scale scores are unknown and do not satisfy normality assumption of parametric statistical techniques. Meaningful addition $X + Y = Z$ requires similar distribution of X and Y and knowledge of distribution of Z. Unknown sampling distribution makes the sample "biased" [35].
- Trait-distances between successive response-categories of an ordinal item are not constant. Equidistant property requires constant value of trait-distance between j-th and $(j+1)$-th levels $\forall\ j$ =1, 2, 3, 4, ….. for measurements of the trait being assessed [36]. Similarly, distance between rungs in *MacArthur Scale of Subjective Social Status* [37] depicting social status in a 10-rungs ladder is not uniform.
- Relationships between *MacArthur SSS Scale* and health outcomes vary for different cultural groups [38].
- Arbitrary classification of total SES scores to various classes/categories without indicating within-class variance and between-class variance fails to indicate efficiency of classification. Socioeconomic Status Composite Scale (*SES-C*) developed by [39] classified total *SES-C* scores into four categories and scores of Financial Distress-Financial Well-Being (*IFDFW)* scale into four interval categories, irrespective of numbers of individuals per category, without giving any measure of classification efficiency.
- Use of Cronbach alpha to find reliability of multidimensional SES-scale without verification of assumptions of Cronbach alpha like tau-equivalent which means equality of all factor loadings. Item-wise factor loadings are usually different [40]. Cronbach alpha gets influenced by outliers and does not work well for multidimensional scales. Misuses of Cronbach alpha are discussed [41-42].
- Construct validity of multidimensional scale as correlation with a chosen criterion scale without verification of similarities of factor structures of the SES-scale and the criterion scale. Validity of multidimensional *SES-C* was found by [39] as correlation with unidmensional *IFDFW* scale. Question arises on representation of which dimension of *SES-C* is validated by the obtained value of $r_{SES-C,IFDFW}$.
- SES changes with time. To address effect of inflation, the income component of *Modified Kuppuswamy scale* and *BG Prasad scale* are updated periodically according to monthly Consumer Price Index for Industrial Workers (CPI-IW) by the Government of India (http://labourbureau.gov.in/LBO_indnum.htm). Thus, quantification of association of SES with CVD-risks by cross-sectional data suffers from limitations.

Proposed methods:

[43] gave method of transforming item scores of SES rating scale (X_i) to continuous equidistant scores (E_i) using data based weights ($W_{ij} > 0$) to j-th level of i-th item satisfying $\sum_{j=1}^{K} W_{ij} = 1\ KW_{ik} - (K-1)W_{i(K-1)} = \text{Constant}\ \forall k = 2, 3, 4, 5, \ldots\ldots$ (Equidistant property)

followed by unit-free $Z_i = \frac{E_i - \overline{E_1}}{SD(E_i)}$ and proposed item score P_i by $P_i = (100-1)\left[\frac{Z_i - MinZ_i}{MaxZ_i - MinZ_i}\right] + 1 \quad \sim N(\mu_i, \sigma_i)$ where $1 \leq P_i \leq 100$. SES-score by arithmetic aggregation i.e., $SES_{AA} = \sum P_i$ ollows normal distribution with mean $\sum_i \mu_i$ and SD $= \sqrt{\sum \sigma_i^2 + 2\sum_{i \neq j} Cov(P_i, P_j)}$ (Method-1). The author also proposed SES index (SES_{c0}) by multiplicative aggregation of ratios of the indicators in the current period $(X_{1c}, X_{2c}, \ldots\ldots, X_{nc})$and the corresponding values in the base period $(X_{10}, X_{20}, \ldots\ldots, X_{n0})$ (Method-2), where $SES_{c0} = \frac{X_{1c}, X_{2c}, \ldots\ldots, X_{nc}}{X_{10}\, X_{20}\, \ldots\ldots X_{n0}}$ where $X_{ic}, X_{i0} > 0$ Each of Method-1 and Method-2 satisfies desired properties in terms of monotonically increasing continuous function, reduction of substitutability among the indicators, not being influenced much by outliers and satisfies the principle of population replication. However, arithmetic aggregation by Method-1 may be preferred since it ensures normality, the basic assumption of many parametric statistical techniques.

Following similar approach, age-specific gender-specific index of CVD-risk factors (I_{CVD-RF_t}) can be obtained by arithmetic aggregation of traditional and new CVD-risk factors in ordinal scale, categorical variables and laboratory generated values and reflecting overall cardiovascular health risk. For categorical variables in CVRFs described by 1, 2, 3, etc. weights are assigned to $\frac{f_j}{n} \times 100$ to get E_i-scores where f_j denotes frequency of the *j*-th level is and *n* is the total sample size. Laboratory generated values in ratio scales are equidistant and such values to be transferred to *Z*-scores.

Properties:

- Each of $I_{CVD-RF_t}$and SES_{AA_t}ensures normally distributed scores. Normality facilitates meaningful aggregation, better ranking, classification and the principle of population replication [44].
  - The indicators can be ranked based on relative importance of *m*-th indicator given by $\frac{\nabla(I_{CVD-RF_t})}{\nabla X_m}$ or$\frac{\nabla(SES_{AA_t})}{\nabla X_m}$ For two successive periods, improvement or decline of $\frac{I_{CVD-RF_t}}{I_{CVD-RF_{(t-1)}}} < 1$ indicates decline. Similarly, improvement/decline of SES_{AA_t}can be computed by the ratio $\frac{SES_{AA_t}}{SES_{AA_{(t-1)}}}$. Decline of I_{CVD-RF_t}or SES_{AA_t}may be probed to identify the indicators where deterioration occurred for possible corrective actions.
- Plot of $\frac{I_{CVD-RF_t}}{I_{CVD-RF_{(t-1)}}}$ (or$\frac{SES_{AA_t}}{SES_{AA_{(t-1)}}}$) for different time periods shows fluctuations of the index across time and facilitate drawing useful inferences about the community in longitudinal set ups.
- Possible to find percentage improvement of each index reflecting responsiveness of measurement of age-specific gender-specific index of CVD-risk factors and SES measurement.
- Critical indicator (*i*-th) requiring managerial attention can be identified as the one for which $\frac{I_{CVD-RFi_t}}{I_{CVD-RFi_{(t-1)}}} < 1$ for I_{CVD-RF_t}or if $\frac{SES_{AAi_t}}{SES_{AAi_{(t-1)}}} < 1$ for SES_{AA_t}

Benefits:

Normally distributed I_{CVD-RF_t} and SES_{AA_t} provide following illustrative benefits:

1.Facilitate estimation of population mean (μ), population variance (σ^2), confidence interval of μ, testing hypothesis like $H_0: \mu_1 = \mu_2$ or $H_0: \sigma_1^2 = \sigma_2^2$ for longitudinal and also for cross-sectional data.

2.Test effectiveness of treatments/cares by H_0: $\mu_{I_{CVD-RF\,Pre-group}} = \mu_{I_{CVD-RF\,Post-group}}$ by paired *t*-test since pre-treatment group and post-treatment group are dependent.

3.Possible to test $H_0: \frac{I_{CVD-RFi_t}}{I_{CVD-RFi_{(t-1)}}} = 0$ or $H_0: \frac{SES_{AAi_t}}{SES_{AAi_{(t-1)}}} = 0$ since ratio of two normally distributed variables follows χ^2 distribution.

4.Equivalency of two scales. Let $f(X)$ and $g(Y)$ denote respectively normal density function of I_{CVD-RF_t}-scores for Scale-1 and Scale-2. One can find equivalent score combinations P_{01} for Scale-1 and P_{02} for Scale-2 by solving the equation $\int_{-\infty}^{P_{01}} f(X)\, dx = \int_{-\infty}^{P_{02}} g(Y)\, dy$ using normal

probability table for a known value of P_{01} [45]. Similarly, equivalent score combinations of SES_{AA_t} can be found.

5.Efficiency of classification may be assessed by lower value of Davies-Bouldin Index (DBI) which considers ratio of within-class and between-classes distances [46]. For K-number of mutually exclusive classes, DBI is computed by

$$DBI_K = \frac{1}{K}\sum_{i=1}^{K}\sum_{j=1\ (i\neq j)}^{K} Max[\frac{DiamC_i - DiamC_j}{\|C_i - C_j\|}]$$

where diameter of *i*-th class $DiamC_i = \sqrt{\frac{\sum_{x_i \in C_i}\|x_i - C_i\|^2}{n_i}}$

C_i: Centroid or mean of the *i*-th class; n_i: Number of members in the *i*-th class.

Upper limit of DBI is 1 and lower value implies better efficiency. The optimal number of clusters characterized by the smallest DBI value can be obtained from the graph of DBI and Number of clusters. DBI is affected by outliers. This is taken care by normally distributed scores of I_{CVD-RF_t} and SES_{AA_t}.

7.Normality enables Principal component analysis (PCA) and computation of factorial validity (FV) as $\frac{\lambda_1}{\sum \lambda_i}$, where λ_1 is the highest eigenvalue associated with the first principal component. Factorial validity from single administration of a test reflects the main factor for which the test was developed and avoids the problems of construct validity [47]. However, factorial validity needs to tally with clinical findings.

1. PCA also enables computation of Cronbach's alpha (α_{PCA}) in terms of λ_1 [48]. Relationships among psychometric qualities:

For a test with *m*-number of standardized items:

- $FV_{Z-scores} = \frac{\lambda_1}{m}$
- Test variance (S_X^2) = $m + 2\sum_{i\neq j=1}^{m} Cov(X_i, X_j)$
- $\alpha_{PCA} = \left(\frac{m}{m-1}\right)\left(1 - \frac{1}{\lambda_1}\right) = \left(\frac{m}{m-1}\right)\left(1 - \frac{1}{FV.\sum \lambda_i}\right) = \left(\frac{m}{m-1}\right)\left(1 - \frac{1}{m.FV_{Z-scores}}\right)$

Thus, higher $FV_{Z-scores}$ increases α_{PCA}

Theoretically defined $r_{tt} = \frac{S_T^2}{S_X^2} = \frac{S_T^2}{\sum \lambda_i + 2\sum_{i\neq j=1}^{m} Cov(X_i, X_j)} = \frac{S_T^2}{\frac{\lambda_1}{FV} + 2\sum_{i\neq j=1}^{m} Cov(X_i, X_j)}$ which

gives non-linear relationship between theoretical reliability and FV of standardized scores, where each term of the denominator can be estimated from data and $S_T^2 = S_X^2 - S_E^2$ where $S_E^2 = \frac{1}{N}[\ \|X_g\|^2 + \|X_h\|^2 - 2\|X_g\|\|X_h\|Cos\theta_{gh}]$ where the scale is dichotomized in *g*-th and *h*-th parallel halves, $\|X_g\|$ and $\|X_h\|$ denotes respectively length of $\boldsymbol{X_g}$ and $\boldsymbol{X_h}$ and θ_{gh} is the angle between $\boldsymbol{X_g}$ and $\boldsymbol{X_h}$ and is given by $Cos\theta_{gh} = \frac{\sum_{i=1}^{N} X_{g_i} X_{h_i}}{\|X_g\|.\|X_h\|}$ [49].

Discussion

The proposed normally distributed indices avoids limitations of CVD-risk models and contribute to improve scoring of instruments relating to age-specific gender-specific index of CVD-risk factors (I_{CVD-RF_t}) and socio-economic status avoiding limitations of ordinal/categorical scores and facilitates parametric analysis for meaningful comparisons, classification, and integration of various scales.

Measures based on correlation are preferred over frequency-based measures of association. Extent of association between I_{CVD-RF_t} with SES_{AA} can be quantified by correlation between $I_{CVD-RF_{i_t}}$ scores and $SES_{AA_{i_t}}$ scores. Prediction of CVD-risk could use regression of I_{CVD-RF_t} on SES_{AA} or multivariate regression of the form $I_{CVD-RF_t} = \alpha + \sum \beta_i SES_{AA_{i_t}}$ and value of R^2 or by canonical correlation analysis where I_{CVD-RF_t} is a vector consisting of p-numbers of CVD-risk factors and SES_{AA} is q-dimensional vector of SES-dimensions/items, even if $p \neq q$.. [50] found good canonical correlation implying association between lifestyle behaviors and CVD-risk factors and the canonical variate scores could predict CHD mortality. Empirical relationship can also be estimated between actual prevalence of CVD (secondary data) or the CVD death rate and the proposed indices I_{CVD-RF_t} and/or SES_{AA} along with fluctuation of association between the two measures across time.

Conclusions:

Relationship between SES and CVD-risks along with identification of critical areas helps to plan medical, social, and economic interventions to mitigate the burden of CHD, particularly among vulnerable groups. Health care professionals and researchers can take advantages of the proposed method to convert scores to normally distributed scores satisfying desired properties, including detection of changes by longitudinal data and better

evaluating psychometric parameters from single administration. Future studies with multi-data set involving longitudinal data may be undertaken for generalization of findings along with psychometric properties of the proposed transformation and to stimulate approach leading to robust and generalizable empirical findings.

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Writing- Original draft preparation, Writing- Reviewing and Editing.

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