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Latent Class Analysis of Behavioral and Metabolic Risk Factors among Patients with Acute Coronary Syndrome

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ABSTRACT

Introduction: The aim of this study was to explore latent classes of risk factors among patients with acute coronary syndrome.

Methods: A cross-sectional study was performed on patients with symptoms of chest pain, unstable angina, or myocardial infarction who had at least one coronary vascular involvement confirmed by angiography. A latent class analysis (LCA) using five categorical risk factors, including metabolic syndrome, physical activity, tobacco use, alcohol, and opium consumption, was conducted on 380 eligible patients. A logistic regression model was used to explore the associations of demographic and clinical variables with latent classes.

Results: The mean age of the patients was 59.05 years (SD= 9.82). A two-class model showed the best fit; Class I (45.1%) was characterized by a high probability of smoking, alcohol, and opium consumption, and Class II was characterized by a high probability of metabolic syndrome (54.9%). There was a significant difference between the two classes in terms of age, sex, job, and educational status. The multiple logistic regression model revealed that age and sex were independent predictors of latent class membership.

Conclusion: This study revealed two distinct latent risk factor patterns among ACS patients emphasizing the need for personalized prevention approaches. Behavioral interventions should be prioritized in younger patients. While, sex-specific metabolic syndrome management strategies should be underscored in older patients.

Key words: Latent class analysis; Acute coronary syndrome; Risk factors; Metabolic syndrome; Behavioral risk factors

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INTRODUCTION

Acute coronary syndrome (ACS), formerly referred to as ischemic heart disease (IHD), has remained the single leading cause of death in both sexes worldwide since 1990.[1] According to the latest report of the Institute for Health Metrics and Evaluation, IHD accounted for 16.2% of total deaths in 2019. It is also the second major cause of disability-adjusted life years (DALYs) and accounts for 6.01% of total DALYs (1). It is projected that deaths due to IHD and stroke, the two main types of cardiovascular disease (CVD),will increase steeply by 2030 and account for 23.6 million deaths annually.[2]

One of the most important ways to control CVD is through a primary prevention strategy to reduce CVD risk factors among people who have already developed cardiovascular risk factors 2. However, the behavioral and metabolic risk factors for CVD are not observed separately and usually influence each other.[3] Previous studies have indicated that an individual-level approach for mitigating risk factors may result in limited success in preventing CVD.[4, 5] Thus, for optimal management of CVD, the likely coexistence of risk factors should be taken into consideration.

Previous studies have shown geographical, ethnic, and sex-based variations in CVD risk factors.[6, 7] Furthermore, the strength of the risk factor–CVD association has also been shown to vary geographically.[8] For example, compared with White Chinese individuals, South Asian individuals had stronger associations of BMI, triglycerides, and HbA1c with CVD than White American individuals did. Given this evidence, it can be postulated that different combinations of risk factors can be detected in different geographic areas.

Latent class analysis (LCA) is a statistical approach utilized to distinguish subjectively diverse subgroups inside populations that regularly share specific outward characteristics.[9] The underlying assumption of LCA indicates that unobserved groups among people known as latent variables can be clarified by a number of indicators that are believed to be useful for categorizing people into these groups. LCA has been applied to detect subgroups of risk factors as latent variables in some chronic diseases, such as hypertension,[10] obesity,[11] and metabolic syndrome.[12] Few studies have used this approach to identify latent classes of risk factors among patients with ACS.[13, 14] Ju and Choi in Korea performed LCA on medical records of patients with coronary heart disease to explore latent classes of modifiable risk factors. They reported heterogeneity in the pattern of risk factors and defined four latent classes, including smoking-drinking, high-risk for dyslipidemia, high-risk for metabolic syndrome, and high risk for diabetes and malnutrition.[14] Jahangiry et al. conducted LCA on patients who underwent coronary artery bypass graft surgery and identified 11 potential risk factors. They identified two classes: premature and nonpremature. The former is characterized by a high probability of smoking, alcohol consumption, opium addiction, and a history of MI, and the latter is characterized by a high probability of obesity, diabetes, and hypertension.[13] The current study is restricted to patients with acute-onset symptoms of coronary artery disease, and we aimed to identify latent classes of ACS patients on the basis of behavioral and metabolic risk factors via LCA.

METHODS

Study type and population

This cross-sectional study was performed on patients presenting with symptoms of chest pain suggestive of ACS referred to the Heshmat referral hospital from 2022--2023. Diagnoses of unstable angina or myocardial infarction were subsequently confirmed through angiography. According to Nylund-GibsonandChoi, at least 300 cases or more are desirable for latent class analysis.[15] A total of 380 patients aged > 30 years who had at least one case of coronary vascular involvement confirmed by angiography were included consecutively to the study. Patients who had stable angina, patent coronary vessels, mild coronary artery diseases, or cardiogenic shock during angiography were excluded from the study.

Ethics approval

The study protocol was approved by the ethical review Board of Guilan University of Medical Sciences: certificate of approval number; IR.GUMS.REC.1400.115. Written informed consent was obtained from all patients to participate in this study.

Latent Class Indicators and instruments

The latent class indicators included physical activity, tobacco status, alcohol consumption, and opium consumption as behavioral risk factors and metabolic syndrome as a metabolic risk factor. Physical activity was measured via a global physical activity questionnaire (GPAQ) developed by the World Health Organization (WHO) for physical activity surveillance in developing countries,[16] which has been shown to have good validity and reliability for assessing physical activity in developing countries with average income.[17] The Persian version of the GPAQ, which is both valid and reliable, is used in many national multicentral surveys of physical activity in Iran.[18] Activity participation in three domains, i.e., work, travel and recreation, as well as sedentary behavior, is measured via 16 questions. For each domain, the activity is measured in terms of the amount of time spent on vigorous or moderate activity. The intensity of physical activity per minute per week was calculated as metabolic equivalents (METs) according to WHO guidelines. The MET values were then categorized as low (MET minutes per week < 600), moderate (MET minutes per week 600--1500), or high (MET minutes per week >1500).[19]

Tobacco status, alcohol consumption, and the use of opium products were measured via a questionnaire adapted from the WHO in the package of essential noncommunicable disease intervention.[20] A dichotomous question regarding the use of tobacco, alcohol, or opium substances was asked of the participants. Tobacco status was defined as consumption of any kind of cigarette, hookah, or tobacco pipe.Opium substances were considered opium, heroin, or cannabis.

Metabolic syndrome was defined as having at least three out of five following risk factors: abdominal obesity (WC>102 cm in males, WC>88 cm in females), triglycerides>150 mg/dl, blood pressure >130/85 mm/Hg, impaired fasting glucose (FBS=102–125), and HDL dysfunction (HDL<40 mg/dl in males and <50 mg/dl in females).[21]

Study variables

Demographic characteristics, dietary information, and clinical variables served as covariates to determine their associations with latent classes. The Dietary Approaches to Stop Hypertension (DASH) diet recommended by Fung et al[22] was used to assess the dietary score of the participants. For this reason, dietary patterns were first measured via 168items of the food frequency questionnaire (FFQ) validated by Mirmiran et al.[23] The FFQ records the frequency of food and beverage intake in a standard serving size on a daily, weekly, monthly, or yearly basis. The intake was then converted to servings per day for 8 components of foods in DASH, i.e., fruits, vegetables, nuts and legumes, whole grains, low-fat dairy, sodium, red and processed meats, and sweetened beverages. The component score was measured according to Fung's method on the basis of participants' quintile ranking on each component. In this method, 1 point was assigned to quintile 1, and 5 points were assigned to quintile 5 for the components of fruits, vegetables, nuts and legumes, whole grains, and low-fat dairy. Sodium, red and processed meats and sweetened beverages were reverse scored.[22] The component scores were then summed to obtain an overall DASH score ranging from 8 to 40, with higher scores indicating a more appropriate diet.

Diabetes was defined as a fasting blood glucose level >126 or the use of antidiabetic drugs. Hypertension was defined as blood pressure >140/90 or the use of blood pressure-lowering medication. A familial history of MI was defined as the occurrence of MI in first-degree relatives, including parents and siblings. Body mass index (BMI) was measured as weight in kg divided by height in meters squared. BMI was then categorized into normal (BMI<25), overweight (25<BMI<30), and obese (BMI>30).

Procedure

The questionnaires were completed by two trained interviewers from patients in the recovery room when the patients became stable after angiography. The interviewers first checked the hospital records of patients to evaluate the eligibility criteria. Upon the approval of the inclusion criteria, the interviewers collected information through study questionnaires, laboratory records, and clinical findings of the patients.

Statistical analysis

The data are presented as the means and standard deviations or frequencies and percentages according to the type of variables. Normality assumption of continuous variables were assessed using Kolmogorov Smirnov test and the homogeneity of variance was evaluated using Leven’s test. Comparisons between groups were made via chi-square tests, t tests or analysis of variance. LCA on categorical variables was used to determine the number of classes via five major categories of variables, including metabolic syndrome, physical activity, tobacco status, alcohol consumption, and opium consumption. In LCA, model estimation is performed via maximum likelihood (ML) via the expectation maximization (EM) algorithm. The relative fit of the model for different numbers of classes was compared via the likelihood ratio chi-square test (G2) followed by information criterion; smaller AIC and BIC values and higher entropy values indicate better fit. The decision on the optimal number of classes was based on the probability for each class >5%, goodness of fit, entropy, parsimony, and interpretability.[24] The classes were then nominated on the basis of their characteristics. The independent associations of demographic and clinical variables with class were explored via a stepwise multiple logistic regression model. Significant variables with $P<0.05$ in the univariate analysis were adjusted as potential confounders. The statistical analysis was performed in Stata version 14. LCA was conducted via the polCA package in R version 4.4.0 (release 2024-04-24).

RESULTS

Demographic and clinical characteristics of the patients

Among the 380 patients, 128 (33.7%) were female, and 252 (66.3%) were male. Table 1 shows the demographic and clinical characteristics of the study participants. The mean age of the participants was 59.05 years (SD= 9.82, min=34, max=87), which was significantly greater in females (60.9 ± 9.7) than in males (58.1 ± 9.8). Males were more likely to be married (86.1% vs 72.7%) and highly educated (31% vs 10%) ($P<0.001$). The prevalence of tobacco status, alcohol, and opium consumption in males was significantly greater than that in females. In contrast, the prevalence of hypertension and diabetes mellitus was significantly greater in females than in males. There was no significant difference between men and women in terms of past or familial history of MI, systolic and diastolic blood pressure, physical activity, or lipid profile. In terms of BMI categories, the frequency of obesity (BMI>=30 kg/m^2) in females was 33.6%, which was approximately twice that in males (19.5%). Similarly, the frequency of abdominal obesity in females (69.5%) was significantly greater than that in males (53.2%). The women had significantly higher FBS and BMI values than the men did. Both abdominal obesity and general obesity were significantly greater in women than in men. The incidence of metabolic syndrome in females was approximately 13% higher than that in males (69.5% vs 56.3%, $P<0.001$).

Classification of latent classes

Five major categories of indicators, including tobacco status, alcohol consumption, opium consumption, metabolic syndrome, and physical activity, were used for latent class analysis. The models progressively increased to five. Table 2 presents the fit indices for latent class models with two to five classes. The two-class model demonstrated the lowest BIC value (2453.7), which is generally preferred for model selection in latent class analysis due to its balance between fit and parsimony. Although the three-class model showed slightly better values for AIC and entropy, the improvement was minimal and did not justify the added complexity. Moreover, the two-class solution provided a more interpretable and conceptually meaningful classification of participants. Given these

Table 1. Demographic and clinical characteristics of the study participants

Characteristics	N(%)	Mean (SD)	Female (N=128)	Male (N=252)	P value
Age (year)	-	59.05 (9.82)	60.9 (9.7)	58.12 (9.8)	0.009
Marriage					0.001
Married	310 (81.6)	-	93 (72.7)	217 (86.1)	
Single/divorce/ widow	70 (18.4)	-	35 (27.3)	35 (13.9)	
Education					0.001
Illiterate	117 (30.8)		60 (46.9)	57 (22.6)	
Primary	172 (45.3)		55 (42.9)	117 (46.4)	
Diploma or higher	91 (23.9)		13 (10.2)	78 (30.9)	
Job status					0.001
Driver	19 (5)		0	19 (7.5)	
Employee	27 (7.1)		4 (3.1)	23 (9.1)	
Farmer	54 (14.2)		7 (5.5)	47 (18.6)	
Freelance	119 (31.3)		4 (3.1)	115 (45.6)	
Housewife	107 (28.2)		106 (82.8)	1 (0.4)	
Unemployed	26 (6.8)		4 (3.1)	22 (8.7)	
Worker	28 (7.4)		3 (2.3)	25 (9.9)	
Tobacco	132 (34.7)		10 (7.8)	122 (48.4)	0.001
Alcohol consumption	44 (11.6)		0	44(17.5)	0.001
Opium products	64 (16.8)		12 (9.4)	52 (20.6)	0.006
Hypertension	194 (51)		86 (67.2)	108 (42.9)	0.001
Diabetes	143 (37.6)		73 (57.03)	70 (27.8)	0.001
MI history	34 (8.95)		9 (7.03)	25 (9.9)	0.351
MI Family history	172 (45.3)		66 (51.6)	106 (42.06)	0.0878
MET minutes per week	1448.3 (1015)		1303 (963)	1521(1035)	0.048
MET categories					0.376
Low	96 (25)		36 (28.1)	60(23.8)	
Medium	126 (33)		45 (35.2)	81 (32.2)	
High	158 (42)		47 (36.7)	111 (44)	
SBP (mmHg)		126.2 (18.9)	127.2 (18.9)	125.8 (18.9)	0.495
DBP (mmHg)		77.3 (11.6)	76.2 (10.7)	77.8 (12)	0.19203
Anthropometric measurement					
Waist (cm)		93.8 (18.7)	93.6 (16.2)	93.8 (19.9)	0.922
Weight (kg)		75.8 (13.0)	71.7 (11)	77.9 (13.4)	0.001
Height (cm)		166.8 (9.4)	160 (6.12)	170 (9.2)	0.001
BMI (kg/m^2)		27.15 (4.2)	27.9 (4.3)	26.8 (4.04)	0.009
BMI categories					0.007
Normal	133 (35)		36 (28.1)	97 (38.6)	
Overweight	154 (41)		49 (38.3)	105 (41.8)	
Obese	92 (24)		43 (33.6)	49 (19.5)	
Abdominal obesity	223 (58.7)		89 (69.5)	134 (53.2)	0.002
Laboratory indices					
FBS (mg/dl)		130.6 (53.9)	141.7 (63)	124.5 (47)	0.003
TG (mg/dl)		177.4 (119)	186 (126)	173 (115)	0.314
HDL (mg/dl)		52.1 (22.1)	53.2 (12.5)	51.5 (25.8)	0.001
LDL (mg/dl)		75 (24.3)	76.7 (22.5)	74.1 (25.2)	0.001
Metabolic syndrome	231 (60.8)		89 (69.5)	142 (56.3)	0.013
DASH score		24.5 (3.9)	23.8 (3.93)	24.8 (3.89)	0.014

Table 2. Model fit indices for the latent class models

Number of Classes	Log-likelihood	AIC	BIC	Entropy	G^2	χ^2	df
2	-1188.3	2402.5	2453.7	0.673.13	54.65	48.87	34
3	-1180.15	2400.3	2479.1	3.110.78	38.42	34.38	27
4	-1176.8	2407.5	2513.9	0.693.09	31.64	26.61	20
5	-1170.9	2409.8	2543.8	0.773.08	19.95	19.14	13

Table 3. Probabilities of latent class membership and behavioral and metabolic risk factors according to latent class

Characteristics	Latent class	
	Class I (HB)	Class II (LB)
Latent class prevalence (%)	45.1	54.9
Metabolic syndrome	0.565	0.643
Physical activity		
Low	0.235	0.267
Medium	0.360	0.308
High	0.405	0.424
Current smoking	0.769	0.000
Alcohol drinking	0.299	0.060
Opium consumption	0.245	0.009

HR-MM, High-risk behavioral moderate metabolic syndrome; LR-HM, Low-risk behavioral high metabolic syndrome

considerations and to maintain model parsimony and clarity in interpretation, the two-class model was retained. G2 and Pearson χ^2 statistics are reported for descriptive purposes. However, given that latent class models often violate the assumptions required for classical significance testing, these statistics were used to examine relative fit across models and to support the selection of the most parsimonious and interpretable solution. The probabilities of class membership and the indicators in each class are presented in Table 3. In total, 45.1% were classified into class I, characterized by high-risk behavioral risk factors, including a high probability of smoking, alcohol, and opium consumption and a medium risk for metabolic syndrome (HB-MM), and class II, characterized by a low risk of behavioral risk factors and a high probability of metabolic syndrome (LB-HM). The level of physical activity was similar in both classes.

Comparison of demographic and clinical characteristics among latent classes

Table 4 shows the associations of demographic and clinical variables with the two latent classes. Sex, age, education, job status, hypertension status, and diabetes status were significantly associated with latent class membership. Patients in class I were remarkably more likely to be male than female (93.1% vs. 6.9%). The mean age of patients in class I was significantly lower than that of patients in class II. The probability of a lower educational level in class II (38.3%) was significantly greater than that in class I (18.6%). Patients in class I were more likely to have freelance jobs and were less likely to be housewives than class II patients were. The prevalence of hypertension and diabetes mellitus in class II patients was significantly greater than that in class I patients.

The results of the stepwise multiple logistic regression model for predicting lateant class membership

Table 4. Comparison of demographic and clinical variables according to the latent classes

P value	Class II (LR-HM)	Class I (HR-MM)	Characteristics
Sex			0.001
Male	135 (93.1)	117 (49.8)	
Female	10 (6.9)	118 (50.2)	
Age (yr.), Mean (SD)	57.1 (10.1)	60.2 (9.5)	0.002
Marriage			0.64
Married	120 (82.8)	190 (80.8)	
Single, divorced or widow	25 (17.2)	45 (19.1)	
Education			0.001
Illiterate	27 (18.6)	90 (38.3)	
Primary	74 (51.03)	98 (41.7)	
Diploma or higher	44 (30.3)	47 (20)	
Job			0.001
Driver	13 (8.97)	6 (2.55)	
Employee	10 (6.9)	17 (7.23)	
Farmer	25 (17.24)	29 (12.34)	
Freelance	64 (44)	55 (23.4)	
Housewife	8 (5.5)	99 (42.1)	
Unemployed	13 (8.9)	13 (5.5)	
Worker	12 (8.3)	16 (6.8)	
MI history	14 (9.7)	20 (8.5)	0.704
Familial History of MI	65 (44.8)	107 (45.5)	0.893
Hypertension	58 (40)	136 (57.9)	0.001
Diabetes mellitus	40 (27.5)	103 (43.8)	0.001
Dash score	24.32 (3.89)	24.6 (3.9)	0.501
BMI categories			0.08
Normal	53 (36.8)	80 (34.04)	
Overweight	65 (45.1)	89 (37.9)	
Obese	26 (18.06)	66 (28.09)	

as dependent variable controlling for potential confounding variables, including age, sex, education, job, hypertension, and diabetes status, revealed that age and sex were independent predictors of class membership. The odds of being in class I among males were 13.04 times greater than those among females (OR=13.4, 95% CI:6.5–26.1; P=0.001). The odds of class I membership decreased with each year of age accrement (OR=0.97, 95% CI: 0.95–0.99; P=0.038).

DISCUSSION

In the present study, which examined behavioral and metabolic risk factors among patients with ACS, two latent classes were identified: HB-MM (class I) and LB-HM (class II). Class I was characterized by a high prevalence of behavioral and moderate metabolic risk factors, while class II exhibited a low prevalence of behavioral but high metabolic risk factors.

Age and sex were independent predictors of class membership; with class I being significantly younger than class II. The finding aligns with a previous study from Iran on patients undergoing

CABG, which also identified two classes distinguished as premature and nonpremature classes.[13] The premature class was characterized by younger age and a higher likelihood of behavioral risk factors, whereas the nonpremature class was associated with older age and metabolic disturbance.

Our findings highlight the critical role of behavioral risk factors, particularly tobacco, alcohol, and opium in younger ages ACS patients. The high prevalence of these risk factors suggests a need for targeted public health interventions to prevent early-onset ACS. Previous studies have also noted the impact of opium consumption in reducing the age of myocardial infarction onset,[25] which may be due to widespread misconception about its supposed cardiovascular benefits.[26] Given that 21% of male patients in our study reported opium use —a figure consistent with prior studies in Iran[27] there is an urgent need to correct misinformation and implement harm-reduction strategies. Furthermore, the underreporting of alcohol consumption due to cultural and legal constraints suggests that the true burden of substance use may be even higher, emphasizing the importance of community-based screening and education programs to address substance-related cardiovascular risks.A previous study revealed a decrease in the prevalence of smoking with increasing age.[28] This finding may indicate the greater importance of smoking as a risk factor for ACS among younger patients.

On the other hand, Class II patients were older and more likely to be female, with metabolic abnormalities playing a dominant role in their ACS risk. This aligns with previous findings indicating sex differences in metabolic syndrome development, driven largely by hormonal regulation of fat distribution.[29] Additionally, a meta-analysis of 37 studies revealed that women with diabetes face a 50% higher relative risk of fatal coronary heart disease compared to men. These findings suggest that sex-specific prevention strategies should be prioritized, particularly in addressing metabolic risk factors among older women.[30]

Our results also align with studies demonstrating geographic and age-related variations in risk factor distributions.[7, 31, 32] For example, research by Tian et al. found that behavioral risk factors had the highest population-attributable fractions for CVD in middle-aged individuals, whereas metabolic risk factors such as hypertension and abdominal obesity were prevalent across all age groups.[32] This underscores the importance of age-stratified prevention strategies, where younger populations may benefit more from behavioral risk reduction programs, while older individuals may require a stronger focus on metabolic control.

Additionally, the significantly lower mean age of ACS onset in our study and a previous research in Iran[33] compared to Western countries (mid-60s to early 70s)[34, 35] raises important public health concerns. While previous explanations have pointed to socioeconomic factors, dietary habits, and physical inactivity,[33, 36] our findings suggest that behavioral risk clustering—particularly high opium use in younger patients—may be a key contributor to the lower mean age of ACS in developing countries. This reinforces the need for comprehensive policy actions, including stricter regulations on opioid availability, enhanced smoking cessation programs, and culturally tailored cardiovascular health education initiatives.

Study Limitations

This study has several limitations. First, given that ACS patients are often unstable emergency cases, laboratory values may not have been collected under standard fasting conditions. However, we addressed this limitation by incorporating medication use (e.g., lipid-lowering and blood pressure medications) into the definitions of dyslipidemia and hypertension. Second, the use of memory-based tools to assess physical activity and dietary patterns introduces potential recall bias. Moreover, we did not collect detailed data on the frequency and duration of tobacco, alcohol, or opium use, which future studies should explore to better understand dose-response relationships.

The cross-sectional nature of this study precludes establishing causality, and the relatively small sample size limited our ability to perform subgroup analyses by sex or ACS diagnosis. Furthermore, as the study was conducted in a referral public hospital, its findings may not fully represent the broader ACS patient population, necessitating careful consideration when generalizing these results.

CONCLUSION

This study highlights distinct latent risk factor patterns among ACS patients, emphasizing the need for personalized prevention approaches. The clustering of behavioral risk factors in younger patients suggests that early-life interventions, including anti-smoking campaigns, substance abuse prevention programs, and lifestyle modifications, should be prioritized. Meanwhile, the predominance of metabolic risk factors in older patients, particularly women, underscores the importance of sex-specific metabolic syndrome management strategies. Given the high prevalence of opium use, public health efforts must also address regional substance use trends and dispel misconceptions about its cardiovascular effects. Future research should explore longitudinal patterns of risk factor evolution to better inform targeted prevention and early intervention strategies.

Conflict of interest

The authors declare no conflict of interest

REFERENCES

1. Institute for Health Metrics and Evaluation (IHME). GBD Compare. Seattle, WA: IHME: University of Washington; 2019 [cited 2023 July 05]. Available from: http://vizhub.healthdata.org/gbd-compare.

2. Benjamin EJ, Blaha MJ, Chiuve SE, Cushman M, Das SR, Deo R, et al. Heart Disease and Stroke Statistics-2017 Update: A Report From the American Heart Association. Circulation. 2017;135(10):e146-e603.

3. Rodrigues da Silva TP, Matozinhos FP, Gratão LHA, Rocha LL, Vilela LA, Oliveira T, et

al. Coexistence of risk factors for cardiovascular diseases among Brazilian adolescents: Individual characteristics and school environment. PLoS One. 2021;16(7):e0254838.

4. Brunzell JD, Davidson M, Furberg CD, Goldberg RB, Howard BV, Stein JH, et al. Lipoprotein management in patients with cardiometabolic risk: consensus conference report from the American Diabetes Association and the American College of Cardiology Foundation. J Am Coll Cardiol. 2008;51(15):1512-24.

5. Mahmood SS, Levy D, Vasan RS, Wang TJ. The Framingham Heart Study and the epidemiology of cardiovascular disease: a historical perspective. Lancet (London, England). 2014;383(9921):999-1008.

6. Ho FK, Gray SR, Welsh P, Gill JMR, Sattar N, Pell JP, et al. Ethnic differences in cardiovascular risk: examining differential exposure and susceptibility to risk factors. BMC Med. 2022;20(1):149.

7. Toms R, Bonney A, Mayne DJ, Feng X, Walsan R. Geographic and area-level socioeconomic variation in cardiometabolic risk factor distribution: a systematic review of the literature. Int J Health Geogr. 2019;18(1):1.

8. Muilwijk M, Ho F, Waddell H, Sillars A, Welsh P, Iliodromiti S, et al. Contribution of type 2 diabetes to all-cause mortality, cardiovascular disease incidence and cancer incidence in white Europeans and South Asians: findings from the UK Biobank population-based cohort study. BMJ Open Diabetes Res Care. 2019;7(1):e000765.

9. Weller BE, Bowen NK, Faubert SJ. Latent Class Analysis: A Guide to Best Practice. Journal of Black Psychology. 2020;46(4):287-311.

10. Kim S, Cho S, Nah EH. The patterns of lifestyle, metabolic status, and obesity among hypertensive Korean patients: a latent class analysis. Epidemiology and health. 2020;42:e2020061.

11. Liberali R, Del Castanhel F, Kupek E, Assis MAA. Latent Class Analysis of Lifestyle Risk Factors and Association with Overweight and/or Obesity in Children and Adolescents: Systematic Review. Childhood obesity (Print). 2021;17(1):2-15.

12. Ahanchi NS, Hadaegh F, Alipour A, Ghanbarian A, Azizi F, Khalili D. Application of Latent Class Analysis to Identify Metabolic Syndrome Components Patterns in adults: Tehran Lipid and Glucose study. Scientific reports. 2019;9(1):1572-80

13. Jahangiry L, Abbasalizad Farhangi M, Najafi M, Sarbakhsh P. Clusters of the Risk Markers and the Pattern of Premature Coronary Heart Disease: An Application of the Latent Class Analysis. Front Cardiovasc Med. 2021;8:707070.

14. Ju E, Choi J. [Identifying Latent Classes of Risk Factors for Coronary Artery Disease]. 2017;47(6):817-27. Article in Korea

15. Nylund-Gibson K, Garber AC, Carter DB, Chan M, Arch DAN, Simon O, et al. Ten frequently asked questions about latent transition analysis. Psychol Methods. 2023;28(2):284-300.

16. Armstrong T, Bull F. Development of the World Health Organization Global Physical Activity Questionnaire (GPAQ). Journal of Public Health. 2006;14(2):66-70.

17. Bull FC, Maslin TS, Armstrong T. Global physical activity questionnaire (GPAQ): nine country reliability and validity study. Journal of physical activity & health. 2009;6(6):790-804.

18. Djalalinia S, Modirian M, Sheidaei A, Yoosefi M, Zokaiee H, Damirchilu B, et al. Protocol Design for Large-Scale Cross-Sectional Studies of Surveillance of Risk Factors of Non-Communicable Diseases in Iran: STEPs 2016. Archives of I3ranian medicine. 2017;20(9):608-16.

19. Prevention of Noncommunicable Diseases Department. Global Physical Activity Questionnaire (GPAQ); Analysis Guide Geneva , Switzerland: World Health Organization; [cited 2024 May 14]. Available from: https://www.who.int/docs/default-source/ncds/ncd-surveillance/gpaq-analysis-guide.pdf?sfvrsn=1e83d571_2.

20. World Health Organization. WHO package of essential noncommunicable (PEN) disease interventions for primary health care [Internet]. Geneva: World Health Organization;2020 (cited 2025 Apr 30]. Available from; https://www.who.int/publications-detail-redirect/who-package-of-essential-noncommunicable-(pen)-disease-interventions-for-primary-health-care

21. Alberti KG, Eckel RH, Grundy SM, Zimmet PZ, Cleeman JI, Donato KA, et al. Harmonizing the metabolic syndrome: a joint interim statement of the International Diabetes Federation Task Force on Epidemiology and Prevention; National Heart, Lung, and Blood Institute; American Heart Association; World Heart Federation; International Atherosclerosis Society; and International Association for the Study of Obesity. Circulation. 2009;120(16):1640-5.

22. Fung TT, Chiuve SE, McCullough ML, Rexrode KM, Logroscino G, Hu FB. Adherence to a DASH-style diet and risk of coronary heart disease and stroke in women. Arch Intern Med. 2008;168(7):713-20.

23. Mirmiran P, Esfahani FH, Mehrabi Y, Hedayati M, Azizi F. Reliability and relative validity of an FFQ for nutrients in the Tehran lipid and glucose study. Public health nutrition. 2010;13(5):654-62.

24. Nylund KL, Asparouhov T, Muthén BO. Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. Structural Equation

Modeling: A Multidisciplinary Journal. 2007;14(4):535-69.

25. Sadeghian S, Graili P, Salarifar M, Karimi AA, Darvish S, Abbasi SH. Opium consumption in men and diabetes mellitus in women are the most important risk factors of premature coronary artery disease in Iran. Int J Cardiol. 2010;141(1):116-8.

26. Roayaei P, Aminorroaya A, Vasheghani-Farahani A, Oraii A, Sadeghian S, Poorhosseini H, et al. Opium and cardiovascular health: A devil or an angel? Indian Heart J. 2020;72(6):482-90.

27. Sadr Bafghi S, Rafiei M, Bahadorzadeh L, Namayeh S, Soltani M, M M, et al. Is opium addiction a risk factor for acute myocardial infarction? Acta Medica Iranica. 2005;43(3).218-222

28. Jousilahti P, Vartiainen E, Tuomilehto J, Puska P. Sex, age, cardiovascular risk factors, and coronary heart disease: a prospective follow-up study of 14 786 middle-aged men and women in Finland. Circulation. 1999;99(9):1165-72.

29. Pradhan AD. Sex Differences in the Metabolic Syndrome: Implications for Cardiovascular Health in Women. Clinical Chemistry. 2014;60(1):44-52.

30. Huxley R, Barzi F, Woodward M. Excess risk of fatal coronary heart disease associated with diabetes in men and women: meta-analysis of 37 prospective cohort studies. Bmj. 2006;332(7533):73-8.

31. Koirala B, Turkson-Ocran RA, Baptiste D, Koirala B, Francis L, Davidson P, et al. Heterogeneity of Cardiovascular Disease Risk Factors Among Asian Immigrants: Insights From the 2010 to 2018 National Health Interview Survey. J Am Heart Assoc. 2021;10(13):e020408.

32. Tian F, Chen L, Qian Z, Xia H, Zhang Z, Zhang J, et al. Ranking age-specific modifiable risk factors for cardiovascular disease and mortality: evidence from a population-based longitudinal study. eClinicalMedicine. 2023;64.

33. Sharif Nia H, Sivarajan-Froelicher E, Haghdoost AA, Moosazadeh M, Huak-Chan Y, Farsavian AA, et al. The estimate of average age at the onset of acute myocardial infarction in Iran: A systematic review and meta-analysis study. ARYA Atheroscler. 2018;14(5):225-32.

34. De Luca L, Marini M, Gonzini L, Boccanelli A, Casella G, Chiarella F, et al. Contemporary Trends and Age-Specific Sex Differences in Management and Outcome for Patients With ST-Segment Elevation Myocardial Infarction. J Am Heart Assoc. 2016;5(12).

35. Mehta LS, Beckie TM, DeVon HA, Grines CL, Krumholz HM, Johnson MN, et al. Acute Myocardial Infarction in Women: A Scientific Statement From the American Heart Association. Circulation. 2016;133(9):916-47.

36. Joshi P, Islam S, Pais P, Reddy S, Dorairaj P, Kazmi K, et al. Risk factors for early myocardial infarction in South Asians compared with individuals in other countries. Jama. 2007;297(3):286-94.