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Machine-learning diet quality score and risk of cardiovascular disease

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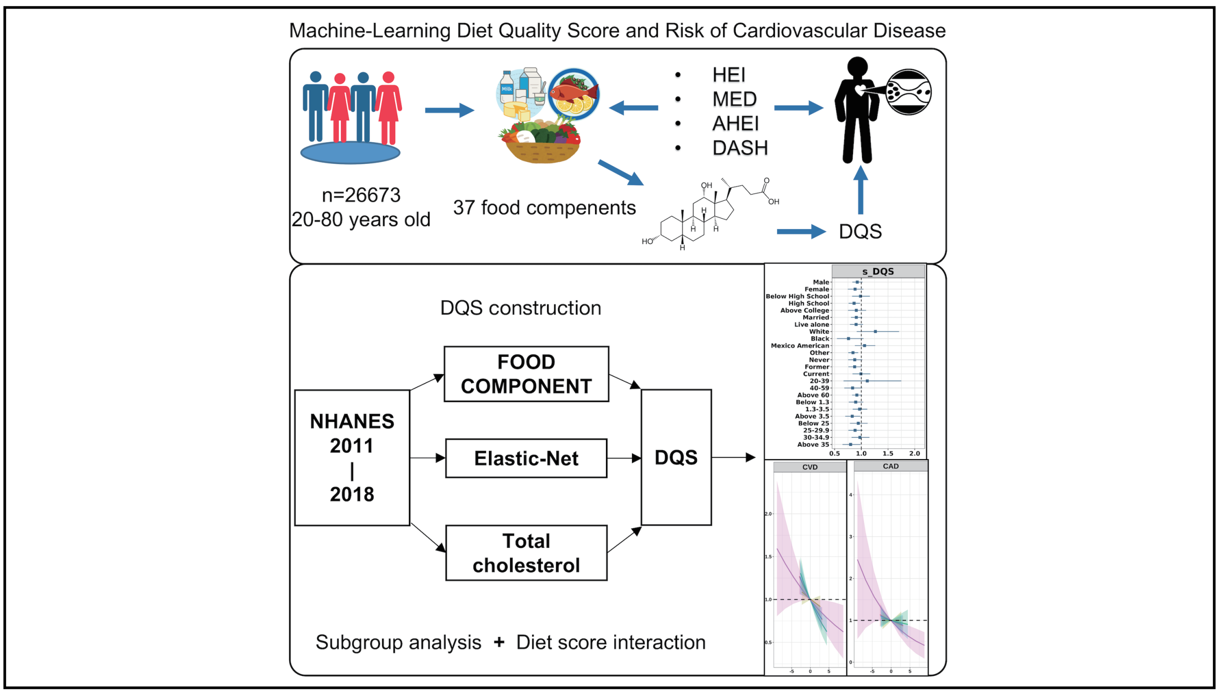
Graphical abstract



A novel machine learning method was introduced to assess diet quality. The newly proposed diet quality score effectively captured distinctive predictive information, independent of existing diet scores, and consistently demonstrated an association with a reduced risk of cardiovascular disease.

Public summary

- A modern machine learning-based diet quality score (DQS), developed using modern machine learning techniques, offers unique and independent insights beyond conventional diet scores, leading to improved dietary recommendations for CAD prevention.
- Higher DQS consistently correlated with a reduced risk of CAD in various NHANES cycles, indicating its potential as a valuable and reliable tool for evaluating and managing CAD risk.
- DQS serves as a powerful complement to existing diet scores, such as the HEI2015, MED, AHEI, and DASH scores, working together to provide more accurate and comprehensive dietary recommendations for CAD patients.

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Abstract: *Objectives*: Various diet scores have been established to measure overall diet quality, especially for the prevention of cardiovascular disease (CVD). Diet scores constructed by utilizing modern machine learning techniques may contain independent information and can provide better dietary recommendations in combination with the existing diet scores. *Methods*: We proposed a novel machine-learning diet quality score (DQS) and examined the performance of DQS in combination with the Healthy Eating Index-2015 (HEI2015), Mediterranean Diet Score (MED), Alternative Healthy Eating Index-2010 (AHEI) and Dietary Approaches to Stop Hypertension score (DASH score). The data used in this study were from the 2011–2012 to 2017–2018 cycles of the US National Health and Nutrition Examination Survey (NHANES). Participants aged above 20 self-reported their food intake and information on relevant covariates. We used an elastic-net penalty regression model to select important food features and used a generalized linear regression model to estimate odds ratios (ORs) and 95% CIs after controlling for age, sex, and other relevant covariates. *Results*: A total of 16756 participants were included in the analysis. DQS was significantly associated with coronary artery disease (CAD) risk after adjusting for one of the other common diet scores. The ORs for DQS combined with the HEI2015, MED, AHEI, and DASH scores were all approximately 0.900, with p values smaller than 0.05. The OR for DQS in the full score model including all other scores was 0.905 (95% CI, 0.828–0.989, p=0.028). Only marginal associations were found between DQS and other CVDs after adjusting for other diet scores. *Conclusions*: Based on data from four continuous cycles of the NHANES, higher DQS was found to be consistently associated with a lower risk of CAD. The DQS captured unique predictive information independent of the existing diet scores and thus can be used as a complementary scoring system to further improve dietary recommendations for CAD patients.

Keywords: diet quality scores; cardiovascular disease; the US National Health and Nutrition Examination Survey (NHANES); machine learning method

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1 Introduction

Cardiovascular diseases (CVDs) are the leading cause of global mortality, accounting for approximately 17.9 million deaths each year[1]. Unhealthy dietary habits have been established as one of the most important risk factors for CVDs[2,3]. Several diet quality scores have been proposed as summary measures to reflect the cumulative effect of food and nutrition components. The Healthy Eating Index (HEI2015)[4], Dietary Approaches to Stop Hypertension score (DASH score)[5,6], Alternative Healthy Eating Index (AHEI)[7,8], and Mediterranean Diet Score (MED)[9,10] are common diet quality scores widely used in practice. The literature has shown that adherence to a healthy eating diet pattern might lower the risk of cardiovascular diseases[11–14]. To our knowledge, no machine learning-based diet quality scores have been proposed. The advantage of the data-driven diet scores is that they may mitigate the possible spurious association or confounding caused by the high correlation between food components and facilitate identification of essential food features from the data. We believe that a data-driven diet score can serve as a complement to the existing diet scores and better provide scientific dietary advice for people with cardiovascular diseases.

In the current paper, we proposed a modern machine learning-based diet quality score (DQS) as a potential summary measure of the cumulative effect of food and nutrition components. By applying an elastic-net variable selection method to diet data from more than 16000 eligible participants in the US National Health and Nutrition Examination Survey (NHANES), DQS was constructed according to plasma total cholesterol (TC), which is used to screen for atherosclerotic risk. Association performance was evaluated with respect to overall CVD, coronary artery disease (CAD) and stroke. Our study showed that combining DQS with existing diet scores might provide dietary recommendations to better mitigate the risk for CVDs, especially for CAD.

2 Materials and methods

2.1 Study population

Data used in this study were collected based on dietary interviews and laboratory measurements from the 2011–2012 to 2017–2018 cycles of NHANES. All the data were downloaded from the NHANES official website (http://www.cdc.gov/nchs/nhanes.htm). The NHANES is a cross-sectional study to assess the health and nutritional status of adults and children in the United States, consisting of an interview section and an examination section. The survey used a 24-hour dietary recall method to collect data on the types and amounts of foods and beverages for Americans. The Food Patterns Equivalents Database (FPED) was used to convert dietary nutrients into the food equivalent pattern components. We collected important demographic covariates, various CVDs, plasma total cholesterol measurements, and 37 food components needed to calculate the HEI2015. Participants with eligible status were included, and those with missing data were excluded from further analysis. NHANES is a public database approved by the Institutional Review Board (IRB) of the National Center for Health Statistics, USA, and all participants signed written informed consent forms. The current study was exempted from IRB review because it included a secondary analysis of de-identified data.

2.2 Assessment of demographic variables

Age was divided into 3 subgroups, consisting of people aged 20–39, 40–59 and older than 60 years. Other covariates included gender (male, female), race/ethnicity (non-Hispanic white, non-Hispanic black, Mexican American people and other (other Hispanic and other race)), education level (less than high school, high school, college graduation and above), marital status (married, living alone), smoking status (never smoked, former smoker, current smoker), poverty income ratio (PIR) (<1.3, 1.3–3.5, >3.5) and body mass index (BMI). BMI was calculated using the formula weight/height^2 (kg/cm^2) and divided into four subgroups (<25, 25–29.9, 30–34.9, >35).

2.3 Assessment of incident CVDs

CAD was defined as having angina or myocardial infarction. Overall CVD was defined as CAD, stroke or congestive heart failure. All relevant endpoints were defined according to the World Health Organization (WHO) International Classification of Diseases, Ninth Revision (ICD-9)[15].

2.4 Assessment of plasma TC

Serum specimens were processed and stored under appropriate frozen (–30°C) conditions until they were shipped to the US National Center for Environmental Health for testing and analysis. Plasma TC was measured using a Roche Modular P chemistry analyzer. Detailed specimen collection and processing instructions are available in the NHANES Laboratory/Medical Technologists Procedures Manual (https://wwwn.cdc.gov/Nchs/Nhanes/2011-2012/TCHOL_G.htm).

2.5 Assessment of dietary quality scores HEI2015, AHEI, DASH and MED

HEI2015, MED, AHEI and DASH scores are four popular diet quality scores widely applied in numerous epidemiological studies. The HEI2015 is the latest iteration of the index designed to align with the 2015–2020 Dietary Guidelines for Americans (DGAs) (https://health.gov/our-work/food-nutrition/previous-dietary-guidelines/2015). In the HEI2015 scoring system, 37 food components are grouped into 9 adequate and 4 moderate component groups. The maximum score for each category is 5 points or 10 points, leading to a total score from 0–100[4]. The MED score was created for a plant-based diet style characterized by high intake of monounsaturated fat, plant proteins, whole grains, and fish; moderate intake of alcohol; and low consumption of red meat, refined grains, and sweets. The range of MED is from 0 to 9[10]. The AHEI is based on foods and nutrients predictive of chronic disease risk, and the total score ranges from 0 to 110[8]. The DASH score, ranging from 8–40, was constructed by assigning larger weights to fruits, vegetables, plant protein from legumes and nuts, moderate weights to low-fat dairy products, and smaller weights to meats, sweets and sodium. A higher score indicates more adherence to a healthier diet style[5]. The amount of food components used to calculate these diet scores was reported by each respondent on days 1 and 2 (within 24 h) from the NHAHES Dietary Data. In the current paper, each food component was divided by total energy intake for further analysis.

2.6 Derivation of DQS

The food components used are provided in Table S1 (see Supporting information). The elastic-net variable selection method (ENET) was used to construct a novel DQS using plasma TC as an intermediate pathway biomarker[16]. Elastic net is a hybrid method of LASSO regression and ridge regression that applies both L_1-norm and L_2-norm regularization to penalize the coefficients in the regression model so that the coefficients of irrelevant variables directly shrink to zero[17]. The DQS was defined as the weighted sum of the nonzero coefficients of the food components derived from the ENET model.

2.7 Statistical analysis

Summary descriptive statistics were calculated according to baseline covariates and the low or high diet score groups of common diet scores. DQS for each participant was constructed based on plasma TC while adjusting for possible confounders. We used the ENET model to determine the most important food components. Tuning parameters were selected by a 5-fold cross-validation procedure. Then, individual DQS was calculated as the weighted sum of food components with nonzero regression coefficients. HEI2015, AHEI, MED and DASH scores were also calculated according to their scoring methods. Both univariate and multiple diet score models were performed to evaluate diet scores on CVD endpoints in scenarios with or without DQS. The odds ratio, 95% confidence interval, and p value were reported. In addition, odds ratios were plotted against the average risk change for every 1/8 increase or decrease in DQS relative to the reference population without incident CVDs. Subgroup analysis was conducted to examine consistency in the magnitude of the effect among different categories of individuals. All the

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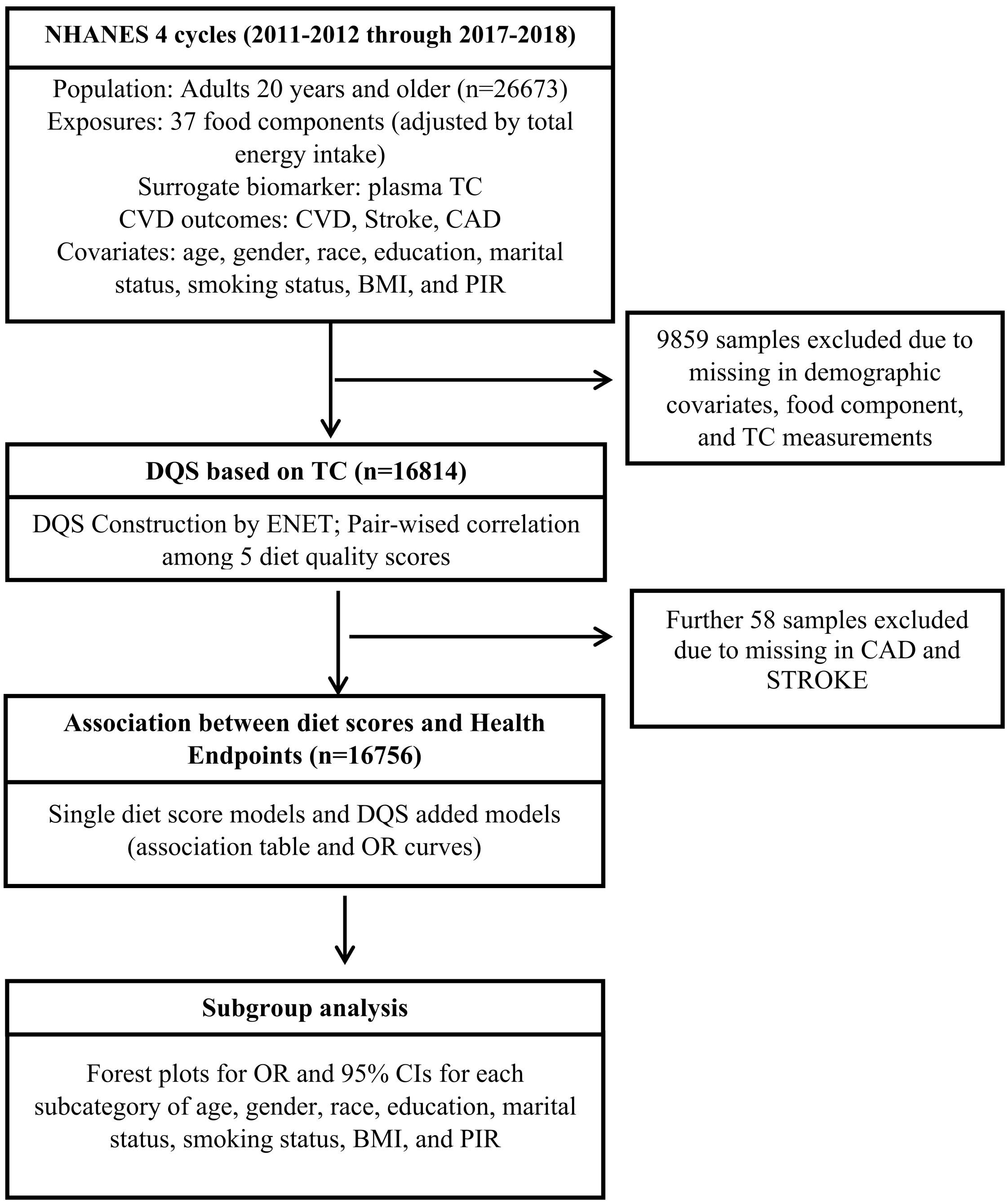

Fig. 1. Schematic diagram of data preprocessing, construction of DQS and analytic methods. CVD: cardiovascular disease; CAD: coronary artery disease; CHF: congestive heart failure; MI: heart attack or myocardial infarction; STROKE: stroke; ENET: elastic net regression.

above analyses were performed using R software version 4.1.2.

3 Results

In total, 16756 participants met the inclusion criteria and were included in the analysis (a schematic diagram of data preprocessing is provided in Fig. 1). Table 1 presents the pooled and stratified baseline demographic characteristics. Means (standard errors) of low and high diet score groups (stratified according to the median diet scores) are 39.44(7.19)/62.15(9.04) for HEI2015, 3.86(0.34)/6.11(0.97) for MED, 39.8(8.95)/63.52(7.07) for AHEI, 22.33(1.6)/28.09(2.57) for DASH and 46.72(2.92)/54.62(5.01) for DQS, respectively. Pairwise correlations among food components are illustrated in Fig. S1. Food components exhibited small to moderate correlations ranging from −0.32 to 0.36. Food predictors selected by ENET are presented in Fig. S2. Correlation

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Table 1. Pooled and stratified baseline characteristics of participants from NHANES 2011–2018. High and low groups were defined according to whether a participant's diet quality score was above the median diet score. Five diet quality scores were included for analysis (HEI2015, MED, AHEI, DASH score and DQS). Percentages of subgroups were calculated for each covariate.

Variable		HEI2015		MED		AHEI		DASH		DQS	
		Low	High	Low	High	Low	High	Low	High	Low	High
Participants		8266	8490	2574	14182	12764	3992	5890	10866	9147	7609
Age (year)	20–39	39.39	29.21	42.54	32.72	36.16	28.08	40.80	30.67	33.62	34.97
	40–59	33.22	33.38	34.42	33.10	33.11	33.92	33.50	33.20	31.84	35.06
	Above 60	27.39	37.41	23.04	34.18	30.73	38.00	25.70	36.13	34.55	29.96
Gender	Male	50.90	46.18	53.11	47.67	49.73	44.61	53.11	46.02	45.75	51.82
	Female	49.10	53.82	46.89	52.33	50.27	55.39	46.89	53.98	54.25	48.18
Education	Below high school	21.62	18.46	23.78	19.33	21.69	14.68	22.43	18.71	20.87	18.99
	High school	59.87	48.66	61.54	52.86	57.54	43.46	61.87	50.03	53.82	54.63
	College or above	18.51	32.89	14.69	27.81	20.77	41.86	15.70	31.26	25.31	26.38
Marital status	Married	57.37	61.67	55.28	60.32	57.93	64.73	55.77	61.60	59.71	59.35
	Live alone	42.63	38.33	44.72	39.68	42.07	35.27	44.23	38.40	40.29	40.65
PIR	Below1.3	36.31	27.59	41.34	30.17	34.86	22.37	38.34	28.39	31.78	32.01
	1.3–3.5	38.70	36.36	37.37	37.54	38.39	34.72	39.03	36.69	39.51	35.12
	Above 3.5	24.99	36.05	21.29	32.29	26.75	42.91	22.63	34.92	28.71	32.87
Race	Non-Hispanic white	13.38	12.99	11.58	13.47	13.61	11.82	12.26	13.68	14.19	11.97
	Non-Hispanic black	9.02	11.15	9.09	10.29	10.13	10.02	8.90	10.76	10.68	9.41
	Mexican American	24.01	19.12	24.01	21.08	23.20	16.21	27.06	18.53	22.06	20.90
	Other	53.58	56.74	55.32	55.15	53.06	61.95	51.78	57.02	53.07	57.72
SMQ	Never	51.74	61.63	47.86	58.36	54.83	62.90	50.20	60.30	60.64	52.07
	Former	22.70	25.14	20.71	24.52	22.9	27.23	21.58	25.21	24.03	23.81
	Current	25.56	13.24	31.43	17.12	22.27	9.87	28.22	14.49	15.33	24.12
BMI (kg/m^2)	Below 25	26.00	30.90	26.46	28.85	26.65	34.34	25.23	30.24	26.89	30.39
	25–29.9	29.32	33.62	29.6	31.84	30.60	34.37	29.24	32.73	30.70	32.46
	30–34.9	22.77	20.51	21.76	21.60	22.55	18.66	22.55	21.12	22.41	20.67
	Above 35	21.91	14.98	22.18	17.71	20.21	12.63	22.99	15.91	20.00	16.48

coefficients between diet scores were calculated and are illustrated in Fig. S1. In general, DQS had small correlations with HEI2015, AHEI, DASH and MED (ranging from 0.08 to 0.15), indicating that DQS may have independent information from the other diet scores. On the other hand, the existing diet scores, such as HEI2015, AHEI, DASH and MED, exhibited moderate to high pairwise correlations ranging from 0.6 to 0.8.

Table 2 shows that higher DQS was significantly associated with lower overall CVD risks, as the estimated OR was smaller than 1 (p=0.046) in the univariate analysis. For specific CVDs, a highly significant association was observed between DQS and CAD (p=0.023). However, the univariate analyses indicated that no significant association was observed between DQS and STROKE. No significant associations between other diet scores and CAD were observed in the current study. The univariate analysis for other scores is presented in Table S2.

In multivariate analysis, the association between DQS and CAD risk remained highly significant after adjusting for other diet scores (all $p<0.05$), suggesting that DQS was independent of other diet scores for predicting CAD risk. Therefore, combining DQS with other common diet scores may further improve the prediction performance with respect to CAD risk. Marginally significant associations between DQS and overall CVD risk were observed after controlling for other diet scores. In the full model, DQS remained significantly associated with CVD and CAD risks after controlling for all other four diet scores (p=0.049 for CVD and p=0.028 for CAD). These results from univariate and multivariate analyses indicated that DQS provided unique information on dietary characteristics that were not captured by other commonly used diet scores. Consistent with the univariate analyses, no significant associations were observed between other diet scores and CAD from the current study.

Fig. 2 shows that CVD risks decreased with DQS scores in both stratified low and high groups according to the other diet scores. As expected, the risks in the high-level diet group (according to the existing diet scores) were lower than those in the low-level diet group. When the DQS scores were lower than the reference (median DQS score of the CVD-free

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Table 2. Odds ratios for DQS under both univariate and multiple regression models combining one of the other diet scores and the full model. All models were adjusted for age, sex, race, education, PIR, marital status, smoking status and BMI.

Model		Cardiovascular endpoint					
		CVD		STROKE		CAD	
		OR (95% CI)	*p*	OR (95% CI)	*p*	OR (95% CI)	*p*
Univariate	DQS	0.949 (0.897–0.983)	0.046	0.928 (0.849–1.011)	0.089	0.903(0.827–0.985)	0.023
Multivariate	HEI2015+DQS	0.947 (0.895–1.002)	0.059	0.925 (0.846–1.009)	0.082	0.902 (0.825–0.984)	0.022
	MED+DQS	0.944 (0.892–0.998)	0.046	0.917 (0.839–1.000)	0.054	0.903 (0.826–0.985)	0.022
	AHEI+DQS	0.941 (0.889–0.994)	0.033	0.918 (0.840–1.001)	0.056	0.901 (0.825–0.983)	0.020
	DASH+DQS	0.947 (0.895–1.001)	0.057	0.926 (0.847–1.009)	0.084	0.903 (0.826–0.985)	0.022
Full model[a]	DQS	0.945 (0.893–0.999)	0.049	0.916 (0.837–1.003)	0.053	0.905 (0.828–0.989)	0.028

[a] Full model: DQS adjusts for all other four diet scores.

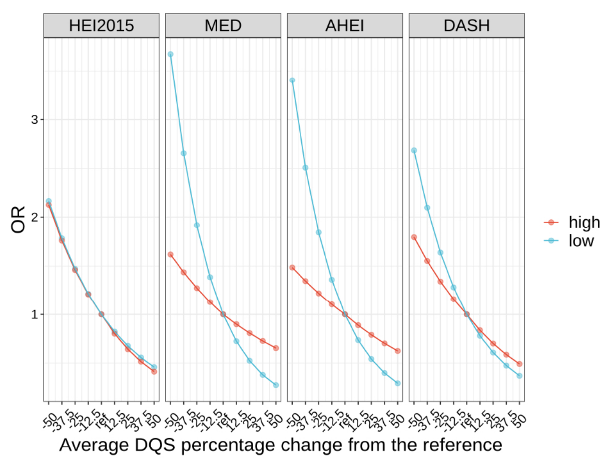

Fig. 2. Odds ratio trends for the population with a 50%, 37.5%, 25%, and 12.5% reduction and a 12.5%, 25%, 37.5% and 50% increase in median diet score DQS relative to the reference population in stratified high and low common diet score groups. Reference diet scores were defined as the median value of DQS without incident CVDs.

group), greater risk reduction rates were consistently observed in the low-diet group than in the high-diet group. This was particularly apparent in the low-diet group according to the MED and AHEI. When the DQS scores were higher than the reference, greater risk reduction rates were still observed in the low-diet group compared to those in the high-diet group. These heterogeneity results indicated that increasing the DQS for the low-diet score group has a greater risk benefit than the high-diet score group. The results for other CVD endpoints are provided in Fig. S3.

Fig. 3 shows the results of the stratified analyses for CAD. Generally, consistent favorable effects of higher DQS (i.e., OR < 1) from either single or multivariate score models were observed across different subgroups. A lower risk of CAD at higher DQS was observed regardless of sex, education, and marital status subgroups. The consistent results from the subgroup analyses demonstrated the robustness of DQS in predicting CAD risks across different subpopulations. Forest plots for other cardiovascular endpoints are provided in Fig. S4.

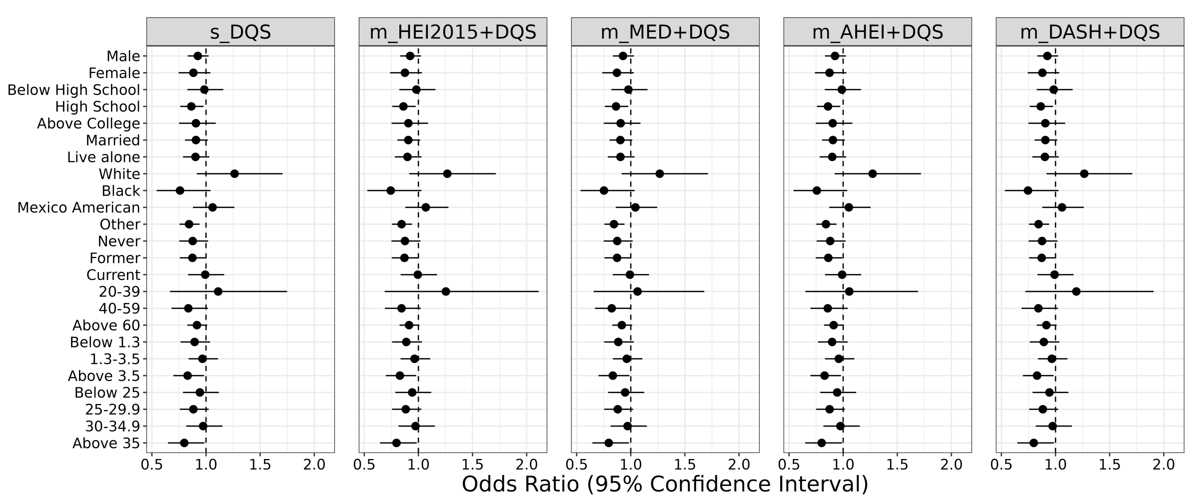

Fig. 3. Stratified analysis for potential risk modifiers including gender, education, marital status, race, smoking status, PIR and BMI. OR and 95% confidence intervals for the univariate diet score model and multiple diet score model for CAD were reported. The columns with "s_" and "m_" refer to the univariate and multiple score regression models, respectively. The "m_HEI2015+DQS" columns refer to the results for DQS in the combined HEI2015 model. Similar explanations for the other columns.

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4 Discussion

There is growing interest in evaluating the health effects of adherence to certain diet patterns, especially cardiovascular disease. Popular diet quality scores have been proposed to quantify an individual's overall diet quality, including the HEI2015, AHEI, MED and DASH scores. The literature has shown that greater adherence to these dietary patterns is associated with a lower risk of CVDs[11–14]. The existing diet scores are well established by evidence from clinical practice. Additional dietary factors were added upon new clinical findings, and diet scores were updated.

In the current paper, we proposed a data-driven diet quality score for various CVDs by using a machine learning method, which is different from most of the existing diet scores. To account for the possible correlation between food components and their complex dose–response to the human body, we adopted the elastic-net machine learning method to identify the most important food components. The underlying logic behind the DQS was to build a predictive diet quality score as a weighted sum of the food components for simultaneous assessment of multiple food components. Weights were determined by the magnitudes of the association between each of the food or nutrient components and the plasma TC levels. We chose TC as the intermediate surrogate biomarker since elevated TC levels have been well-established to be associated with an increased risk of CVD and have been used as one of the most important surrogate biomarkers for diagnosing CVD diseases. Future research may be needed to integrate multiple CVD biomarkers, such as lactate dehydrogenase and myoglobin[16], to further refine DQS and to obtain a more informative diet score.

Our results were generally consistent with previous studies reporting a negative association between diet score and incident CVDs[11–14]. Univariate score analysis showed that the HEI2015, AHEI and DASH scores had slightly better performance than the DQS in predicting the risk of incident CVDs and STROKE. MED scores seemed to be less predictive than the other four diet quality scores. On the other hand, DQS had better overall performance than the existing diet scores in association with CAD risk. The results of the multivariate regression models combining DQS and an established diet score showed that DQS remained statistically significant for CAD after adjusting any of the existing diet scores, indicating that the DQS score carried unique predictive information independent of the current, existing diet scores. The results of the full model showed that DQS remained significant after adjusting for all other 4 diet scores for overall CVD, STROKE and CAD. These results implied that using DQS and the established diet scores together could provide more accurate predictions, especially for CAD.

The findings of the current study suggested that the integration of DQS with commonly utilized dietary scores can offer enhanced dietary management for clinical applications. For instance, in the prevention and control of hypertension while adhering to the DASH dietary pattern, greater attention should be directed toward controlling components that exert a detrimental effect on the DQS score, such as the consumption of added sugar and alcohol. Individuals with lower DASH scores are expected to derive greater CVD health benefits by limiting their intake of components that negatively affect the DQS compared to individuals with higher DASH scores.

Missing data can have an impact on the results. In this particular study, instances with incomplete variables were straightforwardly excluded. To assess the potential influence of excluding data, we randomly removed 10% of the dataset and performed association analysis on the remaining datasets. This process was repeated 100 times, consistently yielding similar results. These findings provide reassurance that the conclusions drawn from the available data are reliable.

5 Conclusions

A novel machine learning-based diet quality score was proposed and assessed. The inverse association suggested that greater adherence to the higher DQS may reduce the risk of incident CVDs. More importantly, after adjusting HEI2015, DASH score, MED and AHEI separately and together, a significant association between DQS and CAD risk still existed, implying that DQS contained information that cannot be explained by the other diet scores. Therefore, better predictive performance can be achieved by applying DQS in combination with common diet scores.

Supporting information

The supporting information for this article can be found online at https://doi.org/10.52396/JUSTC-2023-0067. The supporting information on DQS construction, food components used to construct DQS, and association results is provided.

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Conflict of interest

The authors declare that they have no conflict of interest.

Biographies

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