SPECIFIC AIMS

Substantial research has shown a significantly negative association between screen time and diet quality[1-5]. Heavy television viewers have higher intakes of nutrient-poor and energy-dense foods[1], and have less preference for fresh fruits, vegetables, whole grain, and calcium-rich food[2]. Poor diet behavior can increase cardio-metabolic risk[3] and cause adverse chronic conditions[6]. High-sugar and high-fat foods are the risk factors for high blood pressure, abnormal BMI, high sympathetic arousal, and cortisol dysregulation, which impair stress regulation[7]. However, most of the studies only focus on screen time's impact on children, adolescents, and young adults, while the analysis of older adults has been markedly ignored. Moreover, little research investigates the interconnection between screen time, diet quality, and overall health. Therefore, our team intends to explore the relationship between screen time and diet quality, and how diet quality further affects overall health among older adults aged 65 and older.

In our preliminary exploratory analysis, we analyzed data from UK Biobank, which recruited 490,966 UK participants, aged 37 to 73 years, from 2006 to 2010[8]. Based on the age at recruitment, we have discovered that (1) There are 11270 participants aged 65 and older, 35 nutrient intakes, and 27 of them with less than 50% missing values. (2) There are two variables: time spent on television and time spent on the computer can measure participants' daily screen time. (3) The median time that older adults spent on television are 3 hours/day, while the median time spent on the computer is 1 hour/day. Utilizing this information, we can divide the 10476 observations into two groups based on the median of total screen time - 4 hours/day. (4) Patients' age is significantly positively related to screen time. (5) Both time spent on television and time spent on the computer are negatively correlated to fresh fruit intake and positively correlated to process meat intake, which indicates a negative association between screen time and diet quality. (6) Fresh fruit intake is positively correlated and salt added to food is negatively correlated to overall health rating, providing essential evidence of the positive relationship between diet quality and health outcomes.

Given these findings, we hypothesized that among older adults aged 65 and older (65+), increased daily screen time will impact their diet behaviors and impair their diet qualities, which further causes adverse health outcomes. Specifically, the more time they spend on television or the computer, the fewer fresh fruits and vegetables they are likely to intake, and the more salted, high-sugar, and high-fat food they would intake. Adverse diet patterns will directly result in poor health outcomes.

These hypotheses will be addressed in different statistical and machine learning methods based on secondary analyses of the UK Biobank data with the following Specific Aims:

Specific Aim 1. To investigate the association between time spent on television or computer among older adults and their dietary quality.
Multiple diet quality indices will be used to measure the mean diet score of each observation. ANOVA test will be conducted to compare the mean diet score difference between older adults who spent more than 4 hours of screen time per day and older adults with less than 4 hours per day. Multivariable and mediation analyses will be constructed to examine the relationship by considering confounders: age, sex, height, weight, sleeping duration, alcohol intake, smoking status, and physical activity.

Specific Aim 2. To investigate the association between dietary quality and overall health among older adults aged 65+.
Classification methods will be developed to train the data set based on diet quality indices and other baseline covariates with the labeled overall health rating. The multivariable analysis will be used to investigate the relationship between diet quality score and overall health rating.

We anticipate that this study will reveal the adverse impact that increased screen time has on diet quality, and poor diet quality affects older adults' health outcomes. If the hypothesis is proven, we can control older adults' daily screen time, and purposely adjust the diet pattern for heavy screen time users.

RESEARCH STRATEGY

1 SIGNIFICANCE

The proportion of internet users, among American older adults 65+, has been dramatically increasing from 14% to 73% for the past two decades, and on average, they spent more than half of their daily leisure time, about 4 hours and 16 minutes, in front of the screen[9]. Increased sedentary time and decreased physical activity are directly linked to adverse physical and psychological health outcomes[10,11]. Prolonged exposure to screen time may disrupt sleep patterns and lead to a decrease in the time and energy spent on preparing and consuming healthy meals. Based on previous literature, sedentary time can be categorized as television viewing, computer use, and sitting time[12]. Since sitting time is not able to be obtained from the UK Biobank, we will use television and computer use as screen time measurements. We have previously mentioned that television and computer use is associated with an increased intake of energy-dense, nutrient-poor foods, and beverages, which can negatively impact dietary quality. Therefore, if our hypothesis is proven effective, we can improve older adults' diet quality and overall health conditions by reducing screen time.

2 INNOVATION

During the literature review, we were astonished by the limited study about the screen time impact on diet quality among older adults 65+. Most of the studies concern more about children's or teenagers' screen time and diet issues[1,2]. We assume that researchers are more concerned about adolescents' addiction issues to television and computer use, and neglect the fact that older adults have more opportunities to access electronic devices when they have more leisure time after retirement. Our study will fill the gap in older adults' diet and health problems caused by extended screen viewing. From our study's anticipated results, clinicians can pay more attention to the diet intake of older adults with long screen time, adjust their deficient diet behaviors and improve their health outcomes.

3 RESEARCH PLAN

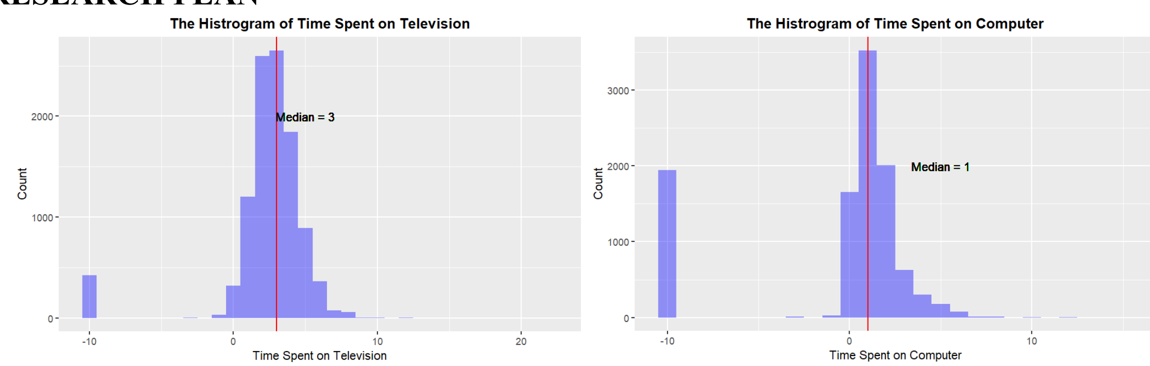


Figure A. The histograms of screen time distribution among older adults 65+

Analysis Preparation. The screen time data, collected from the UK Biobank, is self-reported by participants. The distribution of daily screen time is shown in Figure A. Since the median time of television watching is 3hr/day and computer use is 1hr/day, it is reasonable to split the targeted observations into two experimental groups at 4hr/day. During our preliminary analysis, we also found that screen time was significantly associated with age. That is to say, people become more sedentary, as they aged.

Diet Quality Score Measurement. The most challenging task of this project is to quantitatively measure diet quality. Since no single method can quantify the 35 nutrition intakes, we propose to use multiple verified diet quality indices to create a new diet quality score, considering the variation in diet, each nutrition measurement score, and relative weight to combine all factors. Based on previous research on US Biobank's diet data, we will utilize Mediterranean Diet Score (MDS) as the nutrition measurement index[13-]

[16], while exploring Food Group Variety (FGV) and Protein Sources Variety (PSV) as the variation in participants' diet[17].

Statistical Methods. One-way ANOVA (analysis of variance) has been employed in numerous research to compare the means of two groups for one dependent variable[18], which in our situation, can test if the mean diet scores among heavy and light screen time users are significantly different. Multivariable analysis like linear regression and multi-level logistics regression, which are widely used regression models to estimate the effect between exposure and outcome[13,19], will be used to further explore the association between screen time and diet score, and between diet score and overall health, adjusted for age, sex, and other health-related features.

Data Mining Classification Models. Among various machine learning algorithms, tree-based models like Decision-Tree and Random-Forest are well suited for multi-categories clinical classification problems. Besides coping with missing values, tree-based models combine heterogeneous data types into a single model[20]. Since the overall health rating in UK Biobank has four different rating classes, tree-based models will have satisfactory performance on the diet data.

Specific Aims 1. To investigate the association between time spent on television or computer among older adults and their dietary quality.

Hypothesis. Older adults aged 65+ who spend more than 4 hours per day watching television or using a computer will have lower dietary quality scores, as measured by the diet quality index, compared to those who spend less than 4 hours per day.

Statistical Test. Let S_1 and S_2 be the mean diet quality score of older adults with more than 4 hours of screen time per day and less than 4 hours of screen time per day, respectively. Then, we have

$$\boldsymbol{H_0: S_1 = S_2}$$
$$\boldsymbol{H_A: S_1 \neq S_2}$$

Rationale. To quantify the diet quality, we can construct a diet quality index or improve established indices used in other literature[13-17] to provide a comprehensive measure of overall diet quality, which considers various aspects of diet quality, including the consumption of fruits, vegetables, whole grains, dairy, protein foods, added sugars, saturated fats, and sodium, among others. Using a diet quality index allows for a standardized and objective measure of overall diet quality, which can be compared across different populations and periods. To examine the relationship between time spent on television or computer and dietary quality, we can conduct hypothesis testing to check the difference in dietary quality between two groups based on statistical inference. Then, we can conduct regression analysis to quantify the influence of time on television or computer on dietary quality, adjusting for confounders. Furthermore, we can perform mediation analysis to examine the underlying mechanisms by which time on TV/PC affects dietary quality. We can check whether the relationship between those two is partially or fully mediated by one or more intermediate variables.

Method. In this study section, we first calculate each participant's diet quality score using the improved dietary quality index.

To calculate the Diet Quality Index, we follow a four-step process. First, we perform variable selection and data cleaning. Specifically, we extract 32 diet intake-related variables, drop useless variables such as food type and pilot data, convert character data to numeric data to indicate intake frequency and inspect missing values. Second, we calculate the Mediterranean Diet Score (MDS) using sex-specific medians. Intakes above the median score as 1, and intakes below the median score as 0. Third, we calculate diet variety in two ways: food groups variety (FGV) and protein sources variety (PSV). The FGV is based on five food groups (meat/poultry/fish/egg, dairy, grains, fruits, and vegetables), with each food group being awarded 3 points if at least 1 item from that group is consumed, else 0 points. The PSV is based on four protein sources (meat, poultry, fish, dairy), with 5 points awarded for consuming 3 or more sources, 3 points for consuming 2 sources, 1 point for consuming 1 source, and 0 points for consuming none. Finally, we calculate the Diet Quality Index using the following weights: MDS: FGV: PSV = 80%: 15%: 5%. The formula for calculating the Diet Quality Index is as follows:

$$DQI = (0.8 \times MDS) + (0.15 \times FGV) + (0.05 \times PSV)$$

where DQI represents the Diet Quality Index, MDS represents the Mediterranean Diet Score, FGV represents the food groups variety score, and PSV represents the protein sources variety score.

We then conduct descriptive statistics to summarize the characteristics of two target groups, examining factors such as age, sex, smoking status, alcohol intake, physical activity level, average dietary score, and time spent on TV/PC. We proceed to assess the association between time spent and diet quality by dividing participants into two groups based on their screen time: one with more than 4 hours per day and the other with less than 4 hours per day. The normality of the diet quality score distribution is inspected, and if not satisfied, the Mann-Whitney U test is employed to compare the distributions between the two groups. We also investigate any diet quality score differences between sexes and smoking statuses. Subsequently, a multivariable linear regression analysis is conducted, using the calculated dietary quality score as the dependent variable and an indicator variable for the time, along with potential confounders such as age, sex, physical activity, sleep duration, and smoking status, as independent variables. To address confounding issues, we employ stratification or regression methods.

Furthermore, we conduct the mediation analysis with physical activity as the mediator between time spent on TV/PC and diet quality. We first estimate the direct effect of time on diet quality, controlling for age, sex, height, weight, smoking, sleep duration, alcohol intake, and friend/family visits using a regression model, where physical activity is a covariate. Next, we estimate the indirect effect of time on diet quality, through physical activity using a mediation model, where physical activity is the mediator. Then, to determine whether physical activity mediates this relationship, we test the significance of the indirect effect using a bootstrapping procedure. We generate multiple bootstrap samples from the original data, estimate the indirect effect for each sample, and calculate a 95% confidence interval for the indirect effect. If the CI does not include zero, this indicates the indirect effect is statistically significant, and physical activity mediates the relationship between time and diet quality. Finally, we calculate the proportion of the total effect of time on diet quality that is mediated by physical activity. To inspect the effect measure modifier, we stratify by sex and smoking status to look deeper into the mediation association among different levels.

Results.
Population Profile. Table A. presents the population profile. The table presents data for two groups: Group 0, with less than 4 hours of screen time, and Group 1, with more than 4 hours of screen time. Specifically, Group 0 has a higher mean total metabolic minutes per day (435.3) compared to Group 1 (379.74), and a slightly higher Diet Quality Index (DQI) score (76.83 vs. 76.06). Group 0 has a higher percentage of females (52.58%) compared to Group 1 (40.40%). Group 0 also has a higher percentage of never smokers (56.28%) and a lower percentage of previous smokers (39.79%) and current smokers (3.93%) compared to Group 1, which has 45.29% never smokers, 49.18% previous smokers, and 5.53% current smokers.

Table A. Descriptive analysis of the population profile

	Group 0 (< 4hr)	Group 1 (> 4hr)
N	3918	5295

Mean of		
age_at_recruitment	67.4	67.41
total_met_minites_per_day	435.3	379.74
DQI_score	76.83	76.06
totale_screen_hours_per_day	2.24	5.35
sleep_duration	7.31	7.33
alcohol_intake_frequency	3.4	3.35
standing_height	168.15	169.38
weight	73.28	78.93
frequency_of_friendfamily_visits	3.39	3.33
Percentage of		
female	52.58%	40.40%
never smoke	56.28%	45.29%
previous smoke	39.79%	49.18%
current smoke	3.93%	5.53%

Statistical Test. The Kolmogorov-Smirnov (KS) test indicates that the diet quality score variable does not satisfy normality, leading us to perform the Mann-Whitney U test. We first test the DQI score distribution difference between the two screen time groups, obtaining a p-value of 8.367e-05. We then test the DQI score distribution differences between females and males, yielding a p-value of 0.237. Additionally, we examine the DQI score distribution among current-smoke, previous-smoke, and never-smoke adults, obtaining p-values of 0.111 (previous vs. never), 4.286e-07 (current vs. never), and 9.868e-06 (previous vs. current).

Multivariable Analysis. We conduct a multivariable linear regression analysis using the DQI score as the dependent variable and screen time, sex, age, and other factors as predictor variables. The model's p-value is smaller than 2.2e-16, with coefficient estimates displayed in Table B.

Table B. Coefficient estimates of the linear regression model

	estimate	p-value	
(Intercept)	40.87905	2.50E-08	***
screen_time	-0.58491	0.0152	*
sex_f31_0_01	-1.7437	4.03E-07	***
age_at_recruitment	0.216994	0.0252	*
total_met_minites_per_day	0.002864	2.00E-16	***
sleep_duration	0.036774	0.7429	
alcohol_intake_frequency	0.60806	8.40E-15	***

	estimate	p-value	
standing_height	0.08263	3.95E-05	***
weight	0.042505	7.48E-05	***
frequency_of_friendfamily_visits	0.562365	1.62E-07	***
smoking_status: never: previous	-0.58957	0.0162	*
smoking_status: never: current	-2.7945	4.47E-07	***

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Mediation Analysis. To investigate the mediation effect of screen time and dietary quality through physical activity, we first conduct a total mediation analysis, controlling for age, sex, height, weight, smoking, sleep duration, alcohol intake, and friend/family visits. The results show in Table C.

Table C. Total Mediation estimates of screen time on dietary quality through physical activity

	estimate	95% CI Lower	95% CI Upper	p-value	
ACME	-0.1202	-0.1752	-0.07	<2e-16	***
ADE	-0.5584	-1.1551	-0.08	0.04	*
Total Effect	-0.6787	-1.2451	-0.19	0.04	*
Prop. Mediated	0.1798	0.0686	0.34	0.04	*

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The mediation results after stratifying by sex are shown in Table D.

Table D. Mediation estimates of screen time on dietary quality through physical activity stratified by sex

	estimate	95% CI Lower	95% CI Upper	p-value	
			Female		
ACME (control)	-0.15953	-0.2768	-0.06	<2e-16	***
ACME (treated)	-0.08691	-0.16891	0	0.08	.
ADE (control)	-1.34584	-2.07953	-0.62	<2e-16	***
ADE (treated)	-1.27321	-2.02854	-0.5	<2e-16	***
Total Effect	-1.43275	-2.15049	-0.75	<2e-16	***
Prop. Mediated (control)	0.10694	0.0435	0.23	<2e-16	***
Prop. Mediated (treated)	0.05569	0.00189	0.19	0.08	.
ACME (average)	-0.12322	-2.0008	-0.06	<2e-16	***
ADE (average)	-1.30953	-2.05403	-0.56	<2e-16	***
Prop. Mediated (average)	0.00131	0.03764	0.22	<2e-16	***
			Male		
ACME (control)	-0.08271	-0.15603	-0.02	<2e-16	***
ACME (treated)	-0.14812	-0.24673	-0.07	<2e-16	***
ADE (control)	0.07066	-0.44235	0.55	0.72	
ADE (treated)	0.00526	-0.52833	0.47	0.96	

Total Effect	-0.07746	-0.60647	0.44	0.84	
Prop. Mediated (control)	0.17605	-1.97283	1.85	0.84	
Prop. Mediated (treated)	0.3014	-3.76289	2.75	0.84	
ACME (average)	-0.11541	-0.20277	-0.05	<2e-16	***
ADE (average)	0.03796	-0.48534	0.51	0.8	
Prop. Mediated (average)	0.23873	-2.63652	2.25	0.84	

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The mediation results after stratifying by smoking status are shown in Table E.

Table E. Mediation estimates of screen time on dietary quality through physical activity stratified by smoking status

	estimate	95% CI Lower	95% CI Upper	p-value	
		No smoking			
ACME (control)	-0.1031	-0.1737	-0.04	<2e-16	***
ACME (treated)	-0.078	-0.134	-0.03	<2e-16	***
ADE (control)	-0.3575	-1.0395	0.49	0.32	
ADE (treated)	-0.3324	-1.0176	0.48	0.36	
Total Effect	-0.4355	-1.0986	0.37	0.24	
Prop. Mediated (control)	0.1723	-2.3098	1.69	0.24	
Prop. Mediated (treated)	0.1353	-1.3272	1.66	0.24	
ACME (average)	-0.0905	-0.1442	-0.03	<2e-16	***
ADE (average)	-0.3449	-1.0285	0.48	0.36	
Prop. Mediated (average)	0.1538	-1.8064	1.68	0.24	
		Previous smoking			
ACME (control)	-0.1361	-0.2640	0.04	<2e-16	***
ACME (treated)	-0.2287	-0.3278	-0.15	<2e-16	***
ADE (control)	-0.8934	-1.4902	-0.36	<2e-16	***
ADE (treated)	-0.986	-1.5848	-0.4	<2e-16	***
Total Effect	-1.1222	-1.7321	-0.58	<2e-16	***
Prop. Mediated (control)	0.1171	0.0318	0.35	<2e-16	***
Prop. Mediated (treated)	0.2074	0.1029	0.41	<2e-16	***
ACME (average)	-0.1824	-0.2803	-0.1	<2e-16	***
ADE (average)	-0.9397	-1.5356	-0.38	<2e-16	***
Prop. Mediated (average)	0.1622	0.0763	0.38	<2e-16	***

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Interpretation of Results.
Population Profile. As hypothesized, Group 0 exhibits a higher DQI score than Group 1. Additionally, the two groups display differing levels of physical activity, percentages of females, and smoking statuses, which may be potential confounders.

Statistical Test. Results demonstrate that the DQI score is distributed differently between the two screen time groups. However, there is no significant difference in DQI score distribution between females and males. The DQI score is distributed differently between current-smoke adults and current-non-smoke adults, with no significant difference between previous-smoke and never-smoke individuals.

Multivariable Analysis. Considering all predictors, reducing screen time from more than 4 hours per day to less than 4 hours per day is expected to increase the DQI score by 0.58.

Mediation Analysis. The total mediation results suggest that reducing screen time may improve dietary quality, and physical activity is not the only pathway through which screen time affects diet quality. This is supported by our total effect estimate of -0.68, with an average causal mediation effect of -0.13 and an average direct effect of -0.52.

After we stratified our results by sex to investigate if the relationship between screen time and the DQI varies by gender. We found that among females, the total effect of screen time on the DQI was more substantial, with a value of -1.43. In contrast, among males, the total effect of screen time on the DQI was smaller, with a value of -0.08, but the mediated effect was more significant, with a value of -0.11. Here we got a positive Average direct effect, which is counterfactual. But we noticed this estimate is not significant. And its 95% CI touches a negative value. Therefore, we can also conclude that physical activity accounts for a more substantial proportion of the negative effect of screen time on the DQI in males. Therefore, the relationship between screen time and the DQI is complex and varies by sex.

When we stratified our results by smoking status. The results suggested that the negative effect of screen time on the DQI is more pronounced among individuals who previously smoked, and physical activity plays a more substantial role in mediating this effect. However, the proportion of the mediation effect was similar between the no-smoking and the previous smoking group. Unfortunately, we couldn't analyze the results for current smokers due to a small sample size.

Specific Aims 2. To investigate the association between dietary quality and overall health among older adults aged 65+.

Hypothesis. There is a significant association between diet quality and overall health among older adults aged 65+.

Rationale. To estimate the association between diet quality and overall health status, we rely on a framework of causal inference. Our approach involves fitting a random forest model that uses several variables related to overall health and diet quality as covariates, with overall health as the response. We choose the random forest method for its flexibility in capturing non-linear effects and complex interactions between covariates. After fitting the model, we evaluate the counterfactual overall health status for each individual and calculate the average treatment effect to assess the association between diet quality and overall health status.

Method. We adopted the causal random forest model to investigate the relationship between diet quality and overall health status[21]. Since overall health status can be associated with several factors in the table, we selected baseline covariates in addition to the diet quality index to improve the fitting.

Before implementing the random forest model, we identified 10 covariates potentially associated with overall health ratings, adhering to the critical assumption of our statistical analysis: "No unmeasured confounders." From a pool of 324 variables, we carried out two rounds of variable selection to refine our model.

In the first round, we applied some general rules of feature selection. We discarded variables with a missing rate higher than 10% and variables related to actigraphy and diet. After centering all variables by subtracting their means and scaling them by dividing their maximum absolute values, we discarded variables with a correlation higher than 0.9 and variance smaller than 0.05. After these operations, we retained 36 variables for the second round of variable selection.

We conducted a multilevel logistic regression taking overall health rating as a response and the 36 variables after the first round of variable selection as covariates. For identifiability, we fix the parameter of a class as 0 and obtain the maximum likelihood fit for the rest of the classes in multilevel logistic regression. We have 4 classes in total in overall health rating and therefore, parameters are estimated only with 3 classes. After obtaining the estimated value of coefficients and their standard error, we computed the p-value for them by treating them as normally distributed. This is based on the asymptotic normality of the MLE estimator since we have a sufficiently large dataset.

To address the issue of an imbalanced dataset, we initially applied the NearMiss undersampling technique to create a balanced dataset. Next, we built a random forest model for the classification of overall health ratings using the data on the diet quality index and other selected covariates. The best-performing fitting parameters are chosen through cross-validation. Then we predicted the counterfactual health status of each individual. This will involve manually inputting a counterfactual diet quality index for each individual and predicting the counterfactual health status using the fitted model while keeping the other baseline covariates constant. We evaluated the conditional average treatment effect (CATE) for each individual by determining the difference between their true health status and the predicted counterfactual health status. We then calculated the average CATE for all individuals to determine the average treatment effect (ATE). Both CATE and ATE will be evaluated to assess the causal relationship.

Results.

<u>Baseline Covariates Selection</u>

The selected variables and their p-values for the 3 classes are displayed in Table F.

Table F. Selected variables and their p-values for coefficients in the 3 classes

Variable	P-value for class 1	P-value for class 2	P-value for class 3
Frequency of tiredness in the past 2 weeks	0	0	0
Sex	4.93×10^{-9}	0	0
Standing height	1.45×10^{-5}	1.22×10^{-10}	5.63×10^{-5}
Alcohol intake	4.42×10^{-14}	0	0

Variable	P-value for class 1	P-value for class 2	P-value for class 3
Anxious feeling frequency	0	0	$2.83\times10^{--6}$
Falls in the last year	$1.31\times10^{--4}$	0	0
Weight change with 1 year ago	$8.79\times10^{--5}$	$2.22\times10^{--16}$	$2.88\times10^{--7}$
Wheeze or whistling in the last year	0	0	0
Arm fat free mass	0	0	$2.03\times10^{--8}$
Trunk fat percentage	0	0	$1.33\times10^{--14}$
Number of vigorous activities	0	0	0

These variables have included multiple aspects including body features such as height and sex, emotional status such as anxious feeling frequency, and physical activities such as the number of falls and Number of vigorous activities. All these selected variables are very significant with p-values lower than 0.001 for coefficients across 3 classes. The most significant ones are “Frequency of tiredness in the past 2 weeks”, “Wheeze or whistling in the last year” and “Falls in the last year” with the p-value almost being 0.

Random Forest Classifier

The overall health rating has 4 levels: “Poor”, “Fair”, “Good” and “Excellent”. We applied NearMiss undersampling and created a balanced dataset with a size of 656. The count plots of the overall health ratings before and after undersampling are shown in Figure B.

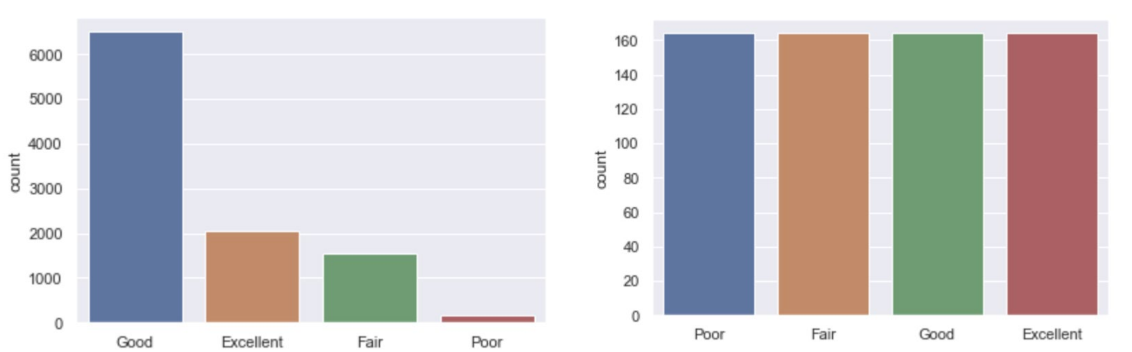
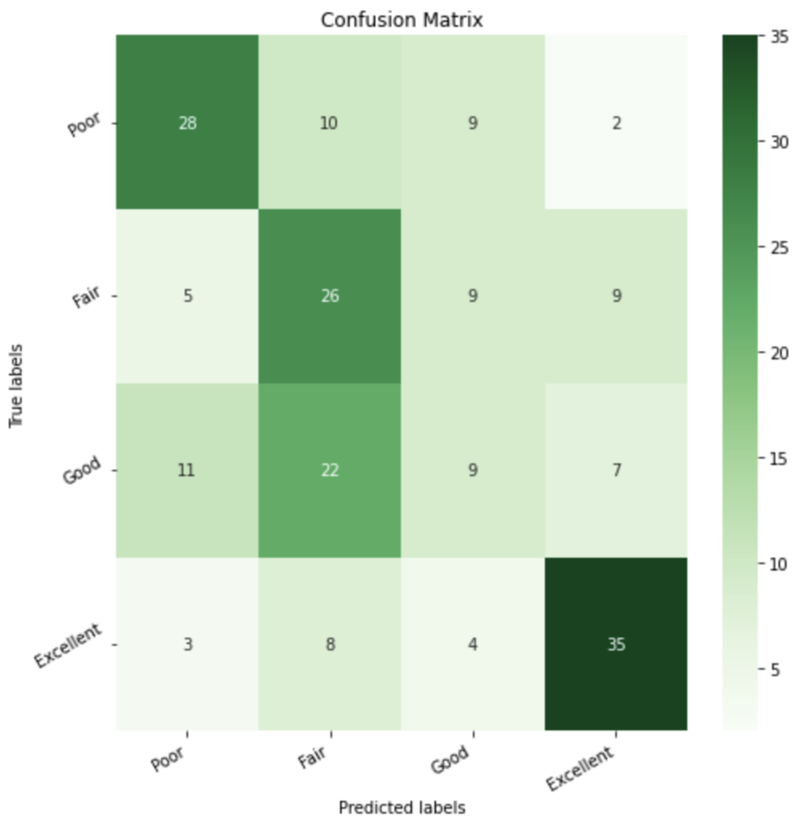


Figure B. Count plots of the overall health ratings

The left plot shows the distribution of overall health ratings before NearMiss undersampling. The plot on the right shows the distribution of overall health ratings after undersampling



	precision	recall	f1-score	support
Poor	0.66	0.70	0.68	50
Fair	0.39	0.53	0.45	49
Good	0.29	0.18	0.23	49
Excellent	0.60	0.57	0.58	49

Figure C. Confusion matrix and classification metrics

Figure D. Frequency polygon of DQI for different overall health ratings

We used a stratified sampling method to split the balanced dataset into training (70%) and testing sets (30%) to make sure that both datasets are balanced in terms of overall health rating. We chose the best parameters based on 5-fold cross-validation using 'GridSearchCV'.

The random forest classifier performs decently well for labeling "Poor" and "Excellent" cases but it struggles with distinguishing between "Fair" and "Good" groups. The confusion matrix and other metrics for the classification are shown in Figure C.

Figure D displays the frequency distribution of DQI for different overall health levels. "Poor" and "Fair" classes have very similar distributions that are more even, while "Good" and "Excellent" classes are similar with more peaked curves.

CATE and ATE

We manually changed the diet quality index to the 2.5 percentile/median/97.5 percentile of population DQI and predict the counterfactual responses. We calculated CATE (conditional average treatment effect) with the following formula:

$$\boldsymbol{CATE_1 = H_{97.5} - H_{median}}$$

$$\boldsymbol{CATE_2 = H_{median} - H_{2.5}}$$

where

$$\boldsymbol{H_{97.5} = RF(DQI_{97.5}; X)}$$

$$\boldsymbol{H_{median} = RF(DQI_{median}; X)}$$

$$\boldsymbol{H_{2.5} = RF(DQI_{2.5}; X)}$$

The percentage of significant CATE is calculated by

$$\boldsymbol{H_{97.5} - H_{median} >= 1}$$

$$\boldsymbol{H_{median} - H_{2.5} >= 1}$$

They are respectively 0.5% and 58.9% (100% "Poor" to "Fair"). ATE, the average of CATE among all individuals are:

$$ATE_{2.5->median} = 0.94$$

$$ATE_{median->97.5} = 0.16$$

Interpretation of Results.

Our study has yielded a substantial quantity of significant variables that may plausibly be linked to an individual's overall health rating. These variables predominantly relate to body morphology, subjective emotional experiences, and physical activities. Notably, the majority of the categories examined have been sufficiently addressed, suggesting that the variables pertinent to an individual's overall health rating are distributed among these categories.

Given that overall health rating is a subjective measure, it may reflect an individual's perception of their health, rather than their objective health status. As a result, variables that directly relate to an individual's sense of wellness, such as the frequency of experiencing tiredness over the past fortnight, the number of instances of wheezing or whistling in the preceding year, and the number of instances of vigorous physical activity lasting over ten minutes, have been found to possess the most notable p-values. Additionally, variables that reflect an individual's emotional state, such as anxious feelings, and those that are indicative of physical impairment, such as the number of falls within the past year, have also been ranked highly in terms of their significance.

There exist multiple variables about bodily characteristics, including but not limited to standing height, fat-free arm mass, and trunk fat percentage. These variables, which are unforeseen outcomes, were not originally considered in our initial hypothesis. The rationale for their eventual inclusion in our study remains unclear at our present stage of research. It is imperative to conduct additional anthropometry studies to elucidate the correlation between these bodily attributes and an individual's overall health rating.

There may be possible associations across these covariates. For example, both sex and alcohol consumption have been proven to be significant. Alcohol consumption is expected to have a difference across males and females. Our choice of random forest model, which detects complex associations between variables by repeated stratification, is thus a reasonably justified method for later analysis.

We can interpret from the results that: Improving the diet quality index from the 2.5 percentile to the median would likely have a causal effect on increasing the overall health rating. However, improving the diet quality index from the median to the 97.5 percentile does not have a significant effect on the overall health rating. Furthermore, DQI becomes less important in terms of the improvement of overall health rating from "Good" to "Excellent".

Conclusion & Discussion

Conclusion and Summary

Combining all the results, we can conclude that older people are more likely to have lower diet quality if they spend more than four hours/day on the television and computer. The effect becomes stronger if they have ever smoked. Compared to females, males' screen time has more impact on diet quality through physical activity. If older people are at poor diet patterns, it is very easy to improve their overall health if they choose to eat healthier: more fresh fruits and vegetables, and less fried and salted food. Unfortunately, if they are having a fine diet pattern, it would be very difficult to improve their overall health even if they significantly improve their diet behaviors. In this scenario, diet will not be the only factor to improve their health.

Limitation and Future Work

There are some limitations to the study. Some collected data are indeterminate. Both nutrient intakes and overall health ratings have unclear definitions. While the nutrient intakes have diverse measurement units, the overall health ratings were self-reported by participants based on the scale: poor, fair, good, and excellent. It is difficult for observations to tell the difference between fair and good. The questionnaire could be designed with more details or objective measurements. The second issue we are concerned about is the missing data of some potential confounders. We are not able to collect social economic data - household income, occupation, and education level from the UK Biobank. Since social economic status can directly affect observations' screen time and diet patterns, our study results may be deviated by confounding.

Another concern about our result is that we do not provide a method to verify our diet score, as it is derived from existing widely used diet quality indices. If collected more new data, we can compare our method with the others based on the accuracy performance. Lastly, the generalizability of the study is limited, as most of the observations are white - British. The results do not apply to other races or countries.

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