Relationship between lifestyle risk factors and development of prediabetes or diabetes, based on BRFSS 2015 questionnaire

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Abstract

This paper is about diabetes...

Keywords: Diabetes, Lifestyle intervention, Causal inference, R-learner, PC algorithm, Regression adjustment

Background

With a staggering 476.0 million prevalent cases, 1.37 million deaths, and 67.9 million disability-adjusted life-years (DALYs) recorded in 2017, diabetes has emerged as a pressing global public health concern. A significant portion of the burden associated with diabetes is believed to be attributable to modifiable lifestyle risk factors, such as diet, smoking, drinking, and physical activity, as suggested by Lin et al. (2021). Therefore, the purpose of this research is to examine the connection between these modifiable lifestyle risk factors and the likelihood of developing prediabetes or diabetes among adults in the United States.

Given the aforementioned background, we have formulated the following research questions:

1. What is the nature of the relationship between lifestyle factors and the risk of developing prediabetes or diabetes?
2. Does this relationship persist even after accounting for covariates?
3. What are the varying effects of lifestyle factors among subgroups characterized by different age, sex, and income levels?

By addressing these research questions, we aim to enhance our understanding of the complex interplay between lifestyle factors and the risk of prediabetes or diabetes, ultimately informing targeted interventions and preventive measures in diverse populations.

Data Preparation

Find Scores with Random Forest

A lifestyle combination score of behavioral factors was constructed using the information of fruits and vegetables consumption, heavy drinking, smoking, and physical activity. It measures the overall healthiness of an individual's lifestyle. This score can be computed by assigning weights to each variable based on their relative importance and then combining the weighted scores. We use the importance function in random forest to compute the importance of the predictor variables in a random forest model. The importance measure is based on the decrease in the node impurity when the variable is used for splitting in the random forest. Then we use the scaled value of the importance to represent the weight. Suppose the importance of each variable is m_1, m_2, m_3, m_4 and m_5 respectively, then the scaled value is $w_i = \frac{m_i}{m_1+m_2+m_3+m_4+m_5}, i = 1, 2, 3, 4, 5$. Based on the results of the literature review, we find that smoking(v_1) and heavy drinking(v_2) will cause diabetes, while more physical exercises(v_3), fruits(v_4) and vegetables consumption(v_5) will reduce the risk of getting diabetes. Thus the combination score is $Score = -w_1v_1 - w_2v_2 + w_3v_3 + w_4v_4 + w_5v_5$. We then convert the continuous variable score into a binary variable. This is achieved through grouping by means of the average. Scores that exceed the mean are set to 1, representing a good lifestyle. Those that fall below the mean are assigned 0, indicating a poor lifestyle.

Table 1: Scoring Weights for Each Covariate

	weighting
HvyAlcoholConsump	81.3077
Smoker	63.2298
PhysActivity	220.4939
Fruits	23.4497
Veggies	46.8822

Data Description

Dataset for this study was collected from the The Behavioral Risk Factor Surveillance System (BRFSS) questionnaire in 2015. BRFSS is a nationwide telephone survey system held by the U.S. Center for Disease Control and Prevention (CDC). It collects data on health-related risk behaviors, chronic health conditions, and preventive services usage among the U.S. residents. This system was initiated in 1984 and updated annually, with more than 400,000 adults being interviewed each year.

The 2015 questionnaire contains three parts, including the core component, optional modules, and state-added questions. The core component consisted of information on demographic characteristics and current health behaviors. The optional modules consisted of topics of health status and behaviors that were not covered in the core set, such as diabetes, immunization, and multiple cancer screening (U.S. CDC).

Based on the BRFSS 2015 dataset, intotal 253,680 survey responses were included. The outcome of interest was a binary variable. It equal to 1 indicated whether being diagnosed with prediabetes or diabetes, and equal to 0 meat no diabetes or only during pregnancy.

In total, 25,3680 participants were enrolled in the study. Among them, 35,346 (14%) were diagnosed with prediabetes or diabetes. Among people who had been diagnosed with prediabetes or diabetes, 48% were male and only 29% had completed college graduate; most of them were elders and with income level between $15,000-$75,000; 75% of them were with high blood pressure and 67% with high cholesterol, and the mean BMI was 32 (SD: 7) kg/m²; 9.2% of them ever had experienced a stroke and 22% with coronary heart disease or myocardial infarction; 96% of them had any kind of health coverage. Among the healthy participants, 43% were male and 44% of them had completed college graduate; most of them were middle-aged adults and 38% of them had the annual income equal or greater than $75,000; only 38% of them had high blood pressure or high cholesterol, respectively, and the mean BMI was 28 (SD: 6) kg/m²; less than 8% of them ever had experienced stroke, coronary heart disease or myocardial infarction; 95% of them had any kind of health coverage. Regarding lifestyles, 55% and 69% of them had the composition score above the mean score of the total population among those who had been diagnosed with prediabetes or diabetes and the healthy, respectively. When specifying different lifestyles, compared with the health participants, more people in the prediabetes/diabetes group ever smoked, were less physically active, and consumed less fruits and vegetables, but less people were heavy drinkers. More details regarding the distribution of these characteristics were displayed in the summary of the dataset (Appendix).

Figure 1 a., b., c. revealed that the distribution of participants' income level, age, and gender varies across different lifestyle combination score categories and diabetes status. This corresponded to our DAG that participants' income level, age and gender may confound the relationship between lifestyles and the development of prediabetes or diabetes.

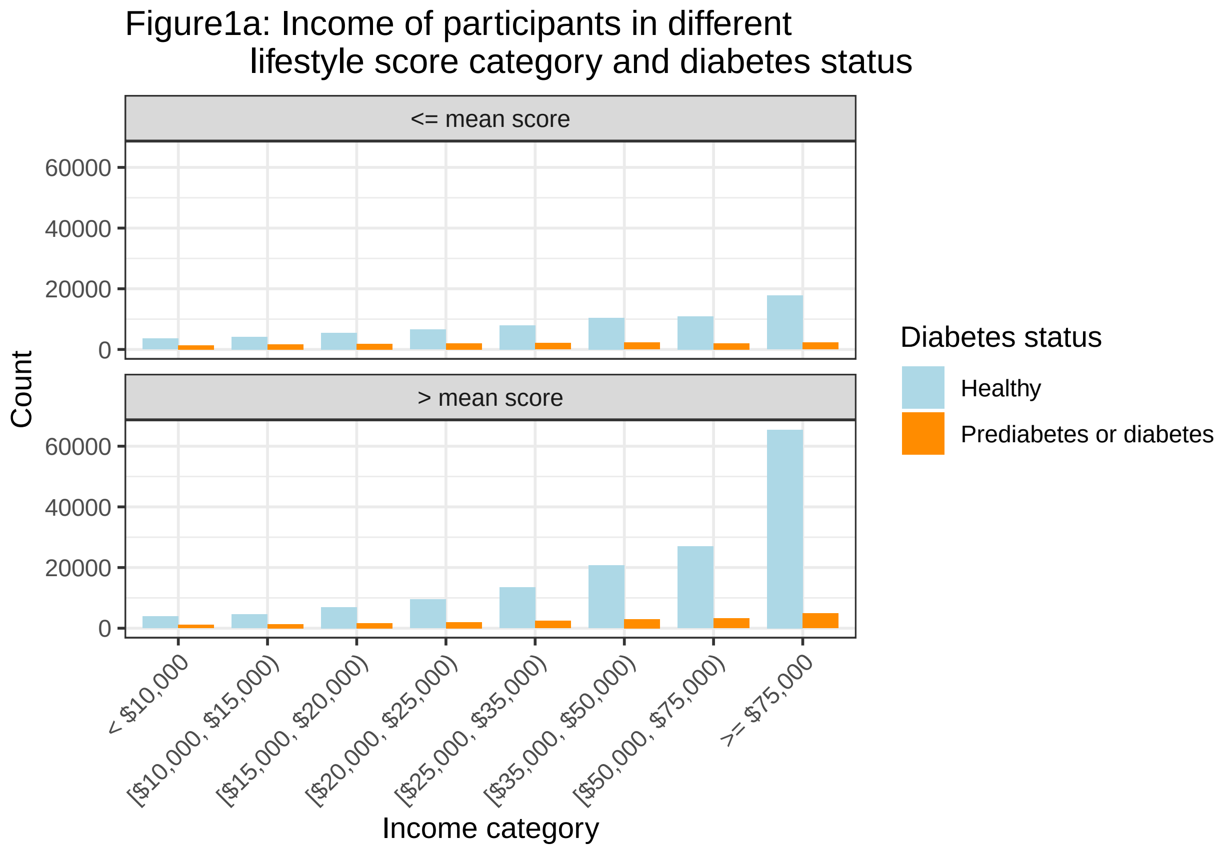


Figure1a: Income of participants in different
lifestyle score category and diabetes status
<= mean score
> mean score
Count
60000
40000
20000
0
Income category
< $10,000
[$10,000, $15,000)
[$15,000, $20,000)
[$20,000, $25,000)
[$25,000, $35,000)
[$35,000, $50,000)
[$50,000, $75,000)
>= $75,000
Diabetes status
Healthy
Prediabetes or diabetes

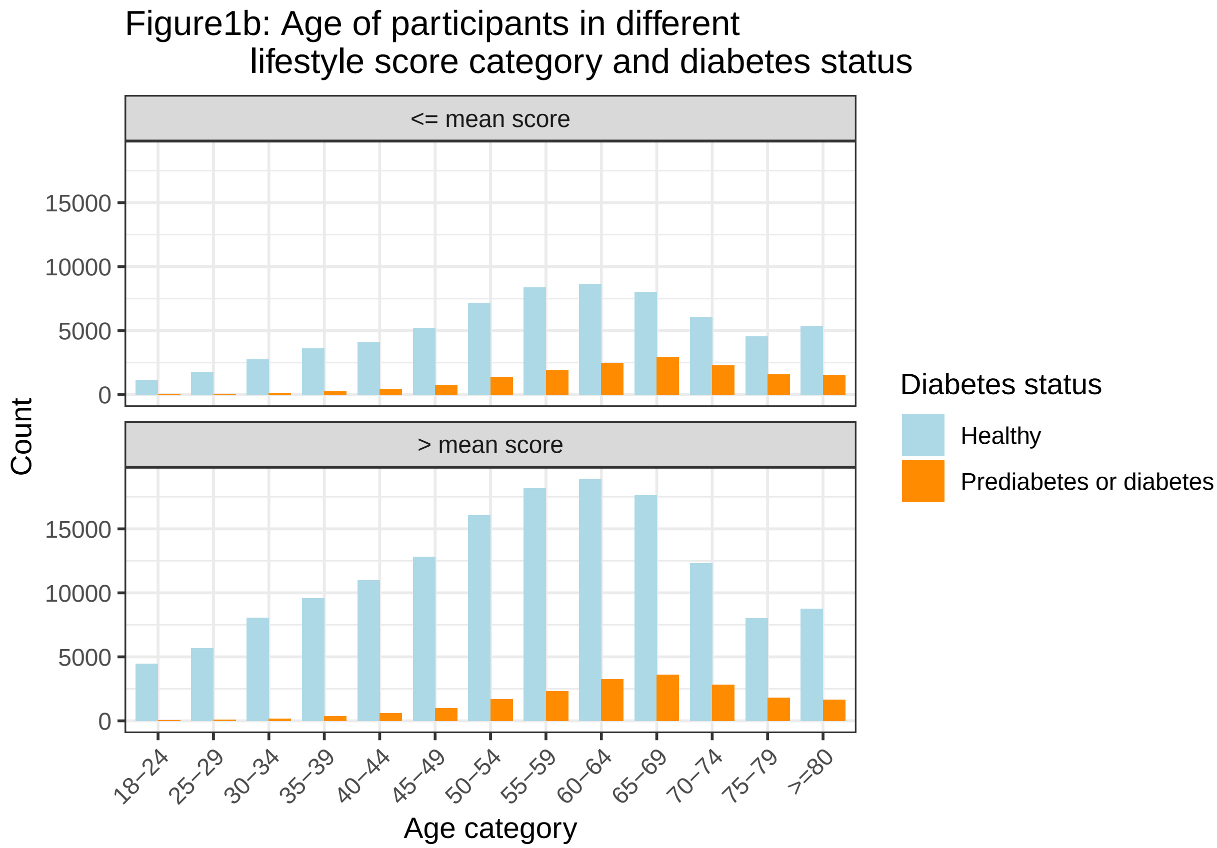
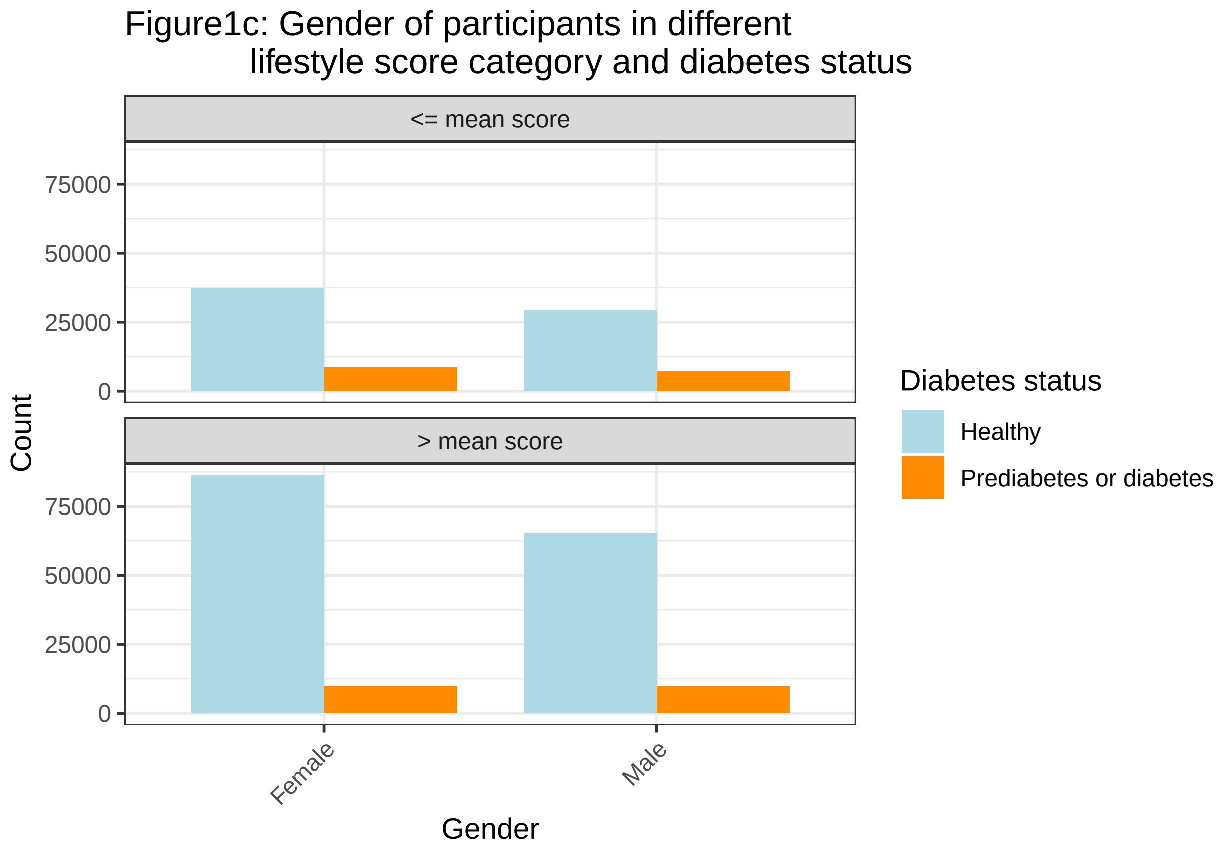


Figure1b: Age of participants in different
lifestyle score category and diabetes status
<= mean score
> mean score
Count
15000
10000
5000
0
18−24
25−29
30−34
35−39
40−44
45−49
50−54
55−59
60−64
65−69
70−74
75−79
>=80
Age category
Diabetes status
Healthy
Prediabetes or diabetes



Methods

Build DAG with PC Algorithm and Literature Review

We initially employ the PC algorithm to determine the relationships between the variables. Prior to running the PC algorithm, we assume that all variables are discrete (as indicated by the data description) and observed. We also assume that the graph is acyclic and adhere to the faithfulness and Markov assumptions. The PC algorithm proceeds as follows (Spirtes et al., 2001): starting with a complete graph, we remove edges between variables X and Y if X and Y are conditionally independent given Z for some (potentially empty) conditioning set. We begin with an empty conditioning set and gradually increase its size. Following these steps, we obtain the skeleton of the graph. Subsequently, we identify immoralities in the graph, whereby if variable W is not in the conditioning set that renders X and Y conditionally independent, the configuration $X - W - Y$ forms an immorality. Then we used the fact that we found all immoralities to orient more edges.

However, we encountered issues with the graph when solely relying on the PC algorithm. For instance, it suggests a direct impact of stroke on income, which is highly implausible. Additionally, we need to determine the directionality of edges based on more reliable sources.

In addition to considering the exposure variables, it is crucial to account for other factors associated with diabetes, such as covariates, precision variables, and confounding variables.

According to Bird et al. (2015), Nanayakkara et al. (2021), and Lin et al. (2021), certain covariates like high blood pressure, stroke, heart disease, and high cholesterol are linked to diabetes, while others like BMI directly affect diabetes. Therefore, a comprehensive assessment and incorporation of these variables is essential when studying diabetes.

From a more reasonable perspective, it is expected that high blood pressure and diabetes, as well as high cholesterol and diabetes, often coexist and influence each other (Schofield et al., 2016 & Peter et al., 2018). Nevertheless, in this analysis, we assume that high cholesterol and high blood pressure impact diabetes for convenience.

Furthermore, confounding variables such as age, gender, and income, as identified by Bird et al. (2015), can influence the relationship between specific exposure variables, covariates, and outcome variables in diabetes research.

To enhance the completeness and practicality of the directed acyclic graph (DAG), we also incorporate potentially unmeasured confounding variables, such as air pollution, and potential precision variables, such as genetics. As highlighted by Ali (2013), while individuals may experience similar environmental exposures, some people are more susceptible to developing diabetes due to genetic factors. Genetics, therefore, is considered a precision variable that exclusively relates to diabetes without affecting other variables.

Logistic Regression with Adjustment

We consider the variable diabetes as the outcome variable, denoted as Y, and the variable score as the treatment variable, denoted as X. Our objective is to estimate the average causal effect of the score on diabetes, which can be expressed as $E[Y(X=1)] - E[Y(X=0)]$.

Before estimating the causal effect, it is essential to examine the association between diabetes and scores. In this case, diabetes takes the value 1 if a person has diabetes and 0 if a person does not have diabetes. Additionally, we assume a linear relationship between the log-odds of diabetes and scores. Hence, it is reasonable to employ a simple logistic model to capture their relationship.

We consider the following model: $\log(\frac{p}{1-p}) = \beta_0 + \beta_1 X$, where p represents the probability of an individual having diabetes, $\frac{p}{1-p}$ represents the odds, and $\log(\frac{p}{1-p})$ represents the log-odds. In this model, X corresponds to the score, and β represents the corresponding coefficients.

Based on the Directed Acyclic Graph (DAG) shown in Graph 1, we observe three confounding paths. These paths indicate that confounding variables, namely age, gender, and income, simultaneously connect diabetes and scores. Consequently, estimating the effect of the score without accounting for these confounding variables would introduce bias. Therefore, it is necessary to determine whether controlling for these confounders would yield better estimates of the parameter of interest.

Using the adjustment criterion proposed by Shpitser et al. (2012), we conclude that adjusting for the three variables (denoted as $Z = \{Z_1, Z_2, Z_3\}$, where Z_1 represents age, Z_2 represents income, and Z_3 represents gender) is sufficient. This adjustment blocks all spurious paths from scores to diabetes and addresses confounding for the three variables. Moreover, it also blocks the confounding path for the variable education. Importantly, this adjustment does not block any of the causal paths from scores to diabetes and does not open any spurious paths. Consequently, we can utilize the non-parametric identification result from the observational distribution, which states that $E[Y(X = x)] = E[E[Y|X = x, Z]]$. Notably, when Z satisfies the adjustment criterion, the conditional ignorability assumption holds, i.e., $Y_x \perp\!\!\!\perp X|Z$. This assumption aids in recovering the causal effect and improving the accuracy of the estimation, as highlighted by Cinelli et al. (2022).

Since we assume a linear relationship between the log-odds of diabetes and scores, age, income, and gender, which aligns with the aforementioned model, the logistic regression for confounding adjustment can be written as $\log(\frac{p}{1-p}) = \beta_0 + \beta_1 X + \gamma_1 Z_1 + \gamma_2 Z_2 + \gamma_3 Z_3$, where γ represents the corresponding coefficients. Consequently, the average causal effect corresponds to the regression coefficient β_1 (Cinelli et al., 2022).

Identity Heterogeneous Effects with R-learner

In this section, we investigate the heterogeneous effects of lifestyle factors on subgroups defined by age, sex, and income using the R-learner (Nie and Wager, 2017). This approach utilizes machine learning to estimate treatment effects in observational studies.

The R-learner is used to estimate the Conditional Average Treatment Effect (CATE), $\tau^*(z_1, z_2, z_3) = E(Y(1) - Y(0) \mid Z_1 = z_1, Z_2 = z_2, Z_3 = z_3)$, with Z_1, Z_2, and Z_3 denoting individual features (age, income, and gender) and Y_i is the observed outcome.

Using the `rlasso` method in `rlearner`, we input age, gender, and income as features, and a categorical score as the treatment variable, with diabetes presence indicating observed response. The algorithm of R-learner also includes cross-validation, we set it with ten folds. Finally, we visualize CATE across income, gender, and age groups.

In the visualization of CATE across different income groups, we observe a correlation between higher income and a larger average treatment effect within the same income bracket. This trend is particularly pronounced among individuals earning over $50,000 annually, where the mean effect significantly surpasses that of other groups.

When comparing CATE across genders, it is noteworthy that the average treatment effect for females is lower than that for males.

The CATE across age groups shows a distinct decline as age increases. For individuals younger than 24, there is little discernible difference in the outcome between those maintaining good or poor lifestyles.

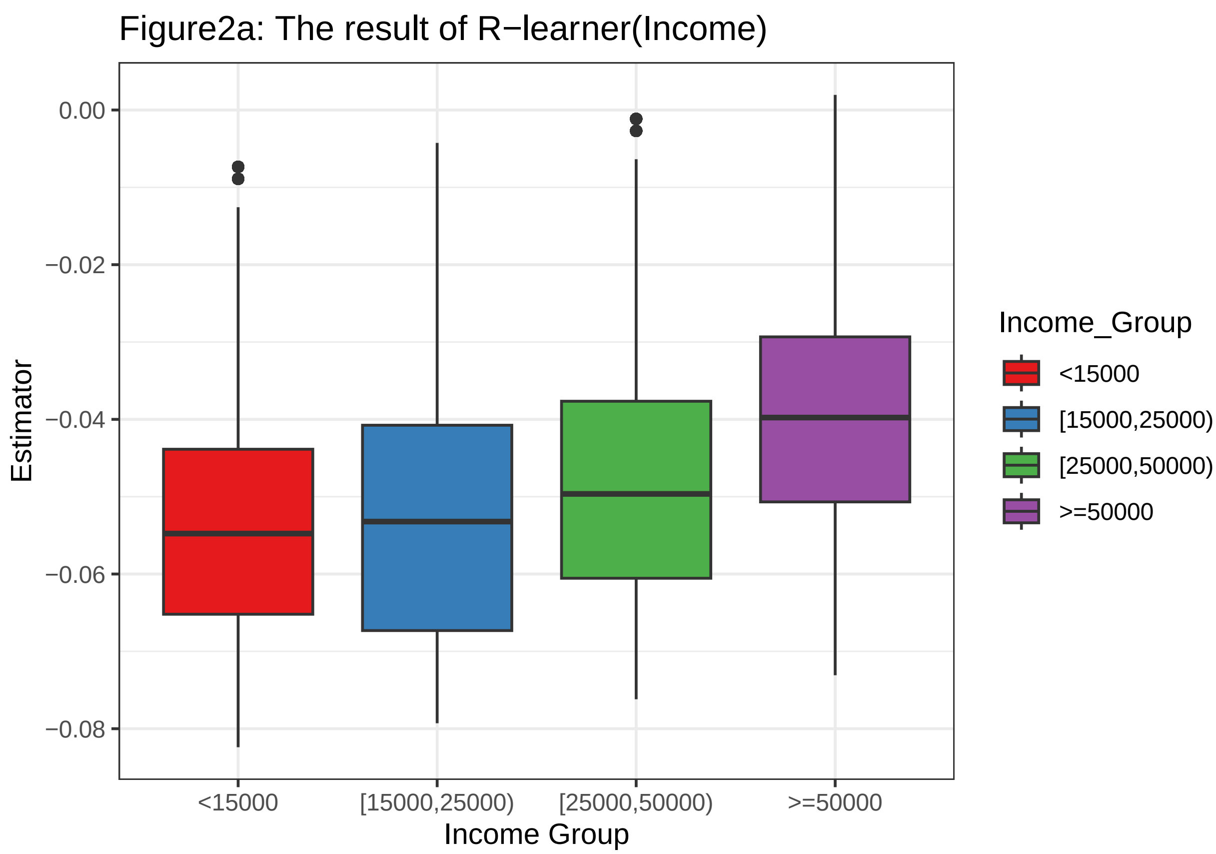


Figure2a: The result of R−learner(Income)
0.00
−0.02
−0.04
−0.06
−0.08
Estimator
<15000
[15000,25000)
[25000,50000)
>=50000
Income Group
Income_Group
<15000
[15000,25000)
[25000,50000)
>=50000

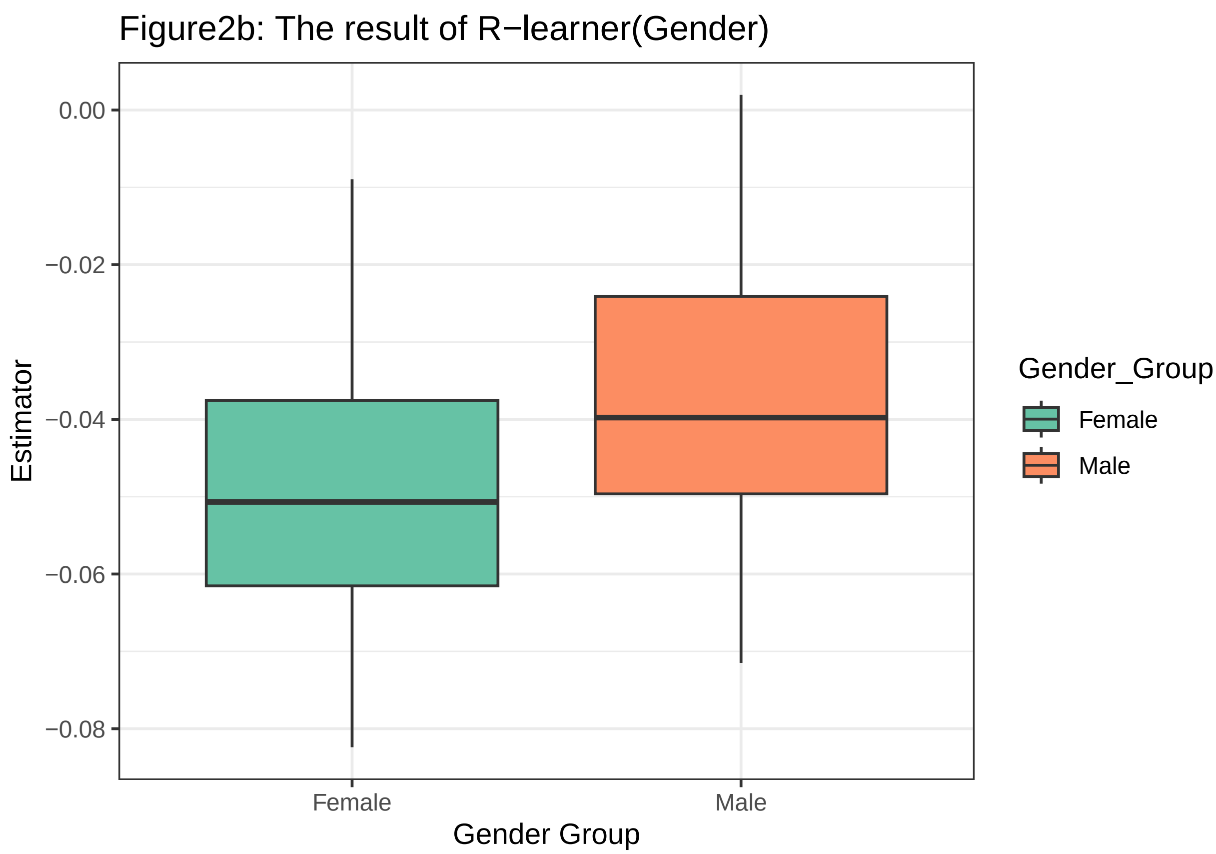
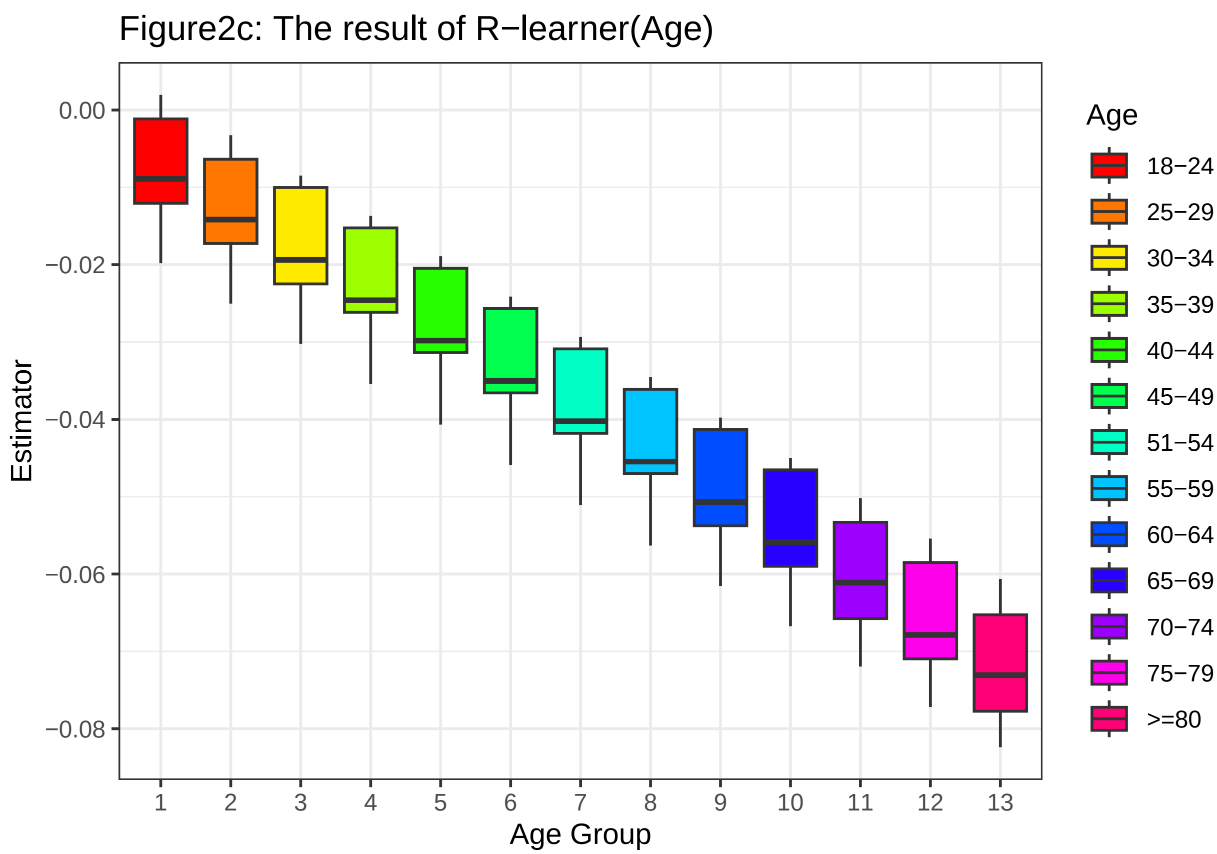


Figure2b: The result of R−learner(Gender)
0.00
−0.02
−0.04
−0.06
−0.08
Estimator
Female
Male
Gender Group
Gender_Group
Female
Male



Results

In the results of logistic regression with adjustment (Table 2), we can see the potential causal effect of the adjusted lifestyle combination score on odds of developing diabetes is 0.6856, which is larger than the coefficient of the unadjusted lifestyle combination score on the odds of diabetes, which is 0.5499.

From the R-learner plots, we discern that higher income individuals are less likely to develop diabetes, even have poor lifestyle choices. This pattern is particularly noticeable for those earning over $50,000 annually. Regarding gender, the difference in diabetes risk between good and poor lifestyle habits is more pronounced in females than males, underscoring the importance of healthy habits for women. In terms of age, the substantial variation in CATE across different age groups suggests that maintaining a healthy lifestyle becomes increasingly vital as one ages. This is because poor lifestyle choices are more likely to induce diabetes as age increases.

Table 2: Adjustment Results

	Estimate	2.5 %	97.5 %
score	0.5499	0.5374	0.5626

	Estimate	2.5 %	97.5 %
adjusted score	0.6856	0.6692	0.7024

Discussion

Target trial

The key causal question we try to answer in this analysis is "whether lifestyle is a risk factor for developing prediabetes or diabetes in healthy participants". Some basic criteria are expected to be satisfied in order to build causality between the exposure and outcome of interest, such as: (1) strength of association, (2) temporality, (3) consistency, (4) dose-response relationship, (5) biologically or theoretically plausible, (6) coherence, (7) specificity, and (8) consensus among experts and the scientific community. The data of this analysis derives from the cross sectional questionnaire of BRFSS program in 2015, which has undermined the ability to build temporality between lifestyles and the development of prediabetes and diabetes. In an ideal situation to answer this causal question, a randomized controlled experiment should be conducted, where healthy participants are assigned to two groups of interventions and remain for a certain period of time, such as 3 years. One group of people are required to adopt healthy lifestyle including all the requirements mentioned below: "lifetime smoking less than 100 cigarettes", "doing physical activity or exercising during the past 30 days other than their regular job", "consume fruit 1 or more times per day", "consume vegetables 1 or more times per day", and "never drinking more than 14 drinks and 7 drinks per week for adult men and adult women, respectively". Another group of people are required to adopt an unhealthy lifestyle, which is a reverse of the requirements in the healthy lifestyle group. All the participants are expected to adhere to their assigned interventions during the whole research period. However in reality, such a randomized trial is inapplicable not only due to ethical constraints, but also due to the limitations of precise definition of "healthy lifestyle" as well as the difficulties to let participants adhere strictly to the assigned lifestyles in everyday life.

In our analysis, a weighted combination score was created by integrating participants' physical activity, smoking history, and alcohol, fruits, and vegetable consumption. Then based on the combination score, participants were grouped as "having the score higher than the mean score of all the participants" or "less than or equal to the mean score of all the participants". We take these categories as a proximation of the interventions that participants may receive in an RCT. However, people in the "higher than mean score" group does not necessarily mean they satisfy all the five requirements for a healthy lifestyle intervention in a RCT. We assume participants with higher than the mean score would in general adopt healthier lifestyles in our analysis. And thus, although we try to approach the true causal effect using this observational study, the effect between lifestyle factors and the risk of developing prediabetes or diabetes that we inferred from this observational study is different from the inference from an RCT.

Refined Management of Diabetes

Based on the estimated heterogeneity in treatment effects among subgroups (defined by factors age, income, and gender), it is clear that different groups respond differently to the treatment. Therefore, we can identify susceptible groups for prioritized preventive measures.

From the perspective of income, it is crucial to pay particular attention to the low-income population. If their lifestyle is subpar and they lack the means to improve their current health status, the impact of their lifestyle becomes even more significant. Looking at it from an age standpoint, middle-aged and elderly individuals inherently have slower metabolic rates compared to younger people. If they continue to maintain unhealthy habits, they are more likely to develop illnesses. In terms of gender, poor lifestyle habits have a greater effect on women. Therefore, it is especially important for women, more so than men, to establish healthy lifestyle habits.

Conclusion

- Healthier lifestyle is associated with lower risk of developing prediabetes or diabetes;
- Limitations exist in cross-sectional studies in inferring causal inference between independent variables and dependent variables;
- We can identify vulnerable groups for prioritized preventive measures based on the heterogeneous treatment effect. We need to pay particular attention to the low-income population, women, and middle-aged to elderly individuals.

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Appendix

Summary of the dataset

Characteristic	**0**, N = 218,334	**1**, N = 35,346	**p-value**
Gender	94,771 (43%)	16,935 (48%)	<0.001
5-year age category			<0.001
18-24	5,622 (2.6%)	78 (0.2%)	
25-29	7,458 (3.4%)	140 (0.4%)	
30-34	10,809 (5.0%)	314 (0.9%)	
35-39	13,197 (6.0%)	626 (1.8%)	
40-44	15,106 (6.9%)	1,051 (3.0%)	
45-49	18,077 (8.3%)	1,742 (4.9%)	
50-54	23,226 (11%)	3,088 (8.7%)	
55-59	26,569 (12%)	4,263 (12%)	
60-64	27,511 (13%)	5,733 (16%)	
65-69	25,636 (12%)	6,558 (19%)	
70-74	18,392 (8.4%)	5,141 (15%)	
75-79	12,577 (5.8%)	3,403 (9.6%)	
>=80	14,154 (6.5%)	3,209 (9.1%)	
Education			<0.001
Never attended school or only kindergarten	127 (<0.1%)	47 (0.1%)	
Elementary	2,860 (1.3%)	1,183 (3.3%)	
Some high school	7,182 (3.3%)	2,296 (6.5%)	
High school graduate	51,684 (24%)	11,066 (31%)	
Some college or technical school	59,556 (27%)	10,354 (29%)	
College graduate	96,925 (44%)	10,400 (29%)	
Income			<0.001
< $10,000	7,428 (3.4%)	2,383 (6.7%)	
[$10,000, $15,000)	8,697 (4.0%)	3,086 (8.7%)	
[$15,000, $20,000)	12,426 (5.7%)	3,568 (10%)	
[$20,000, $25,000)	16,081 (7.4%)	4,054 (11%)	
[$25,000, $35,000)	21,379 (9.8%)	4,504 (13%)	
[$35,000, $50,000)	31,179 (14%)	5,291 (15%)	
[$50,000, $75,000)	37,954 (17%)	5,265 (15%)	
>= $75,000	83,190 (38%)	7,195 (20%)	
Lifestyle composition score			<0.001
<= mean score	66,891 (31%)	15,745 (45%)	
> mean score	151,443 (69%)	19,601 (55%)	
Have smoked at least 100 cigarettes lifetime	94,106 (43%)	18,317 (52%)	<0.001
Physical activity in past 30 days (not including job)	169,633 (78%)	22,287 (63%)	<0.001
Consume fruit >= 1 times per day	140,205 (64%)	20,693 (59%)	<0.001

Characteristic	**0**, N = 218,334	**1**, N = 35,346	**p-value**
Consume vegetables >= 1 times per day	179,105 (82%)	26,736 (76%)	<0.001
Heavy drinkers	13,424 (6.1%)	832 (2.4%)	<0.001
High blood pressure	82,225 (38%)	26,604 (75%)	<0.001
High cholesterol	83,905 (38%)	23,686 (67%)	<0.001
BMI			<0.001
Mean(SD)	28(6)	32(7)	
Ever had a stroke	7,024 (3.2%)	3,268 (9.2%)	<0.001
Coronary heart disease or myocardial infarction	16,015 (7.3%)	7,878 (22%)	<0.001
Any health coverage	207,339 (95%)	33,924 (96%)	<0.001

Definition (adjustment criterion (Shpitser et al., 2012))

A set of variables Z in the adjustment set satisfies the adjustment criterion relative to (X, Y) in a DAG G if:

- No element in Z is a descendant in $G_{\bar{x}}$ (the DAG G without the edges with arrows coming into X) of any $W \notin X$ which lies on a proper causal path from X to Y.
- All non-causal paths in G from X to Y are blocked by Z.

DAG