The Impact of Sleep Trouble and Other Lifestyle and Health Factors on HDL Cholesterol: Insights from Multiple Linear Regression Analysis

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ABSTRACT

This study explores how lifestyle behaviors and health factors influence total cholesterol levels, with a focus on the interaction between sleep troubles and long-term lifestyle habits. NHANES data from adults aged 20-59 with complete covariate measurements were analyzed using multiple linear regression (MLR). Interaction terms evaluated how lifestyle factors modify the effect of sleep troubles on cholesterol. Results showed that habitual physical activity reduced the effect of sleep troubles on cholesterol by 0.35 mg/dL ($p=0.001$), and regular marijuana use reduced it by 0.21 mg/dL ($p=0.093$). Diabetes was associated with a 0.41 mg/dL decrease in cholesterol ($p<0.001$), while hard drug use increased it by 0.26 mg/dL ($p<0.001$). Depression had no significant association ($p=0.24$). Findings suggest that long-term behaviors like physical activity and marijuana use influence the relationship between sleep troubles and cholesterol.

1. BACKGROUND

High-Density Lipoprotein (HDL) cholesterol, often called "good cholesterol," plays a vital role in cardiovascular health by removing excess cholesterol from the bloodstream. The primary goal of this study is to examine how lifestyle factors (e.g., physical activity, smoking, alcohol consumption) and health conditions (e.g., depression, sleep trouble) are associated with total cholesterol levels adjusted for potential confounders. Evidence suggests that sleep disturbances can affect lipid metabolism (Schmid et al., 2015), potentially altering the impact of lifestyle behaviors such as physical activity, alcohol use, smoking, and marijuana use on HDL cholesterol. This study aims to explore the interactions between habitual lifestyle behaviors and sleep trouble to understand their combined effects on cholesterol levels. By focusing on habitual lifestyle behaviors, we aim to capture true associations and minimize biases related to short-term variability.

2. METHODS

2.1. Study Population

This study utilizes data from **the National Health and Nutrition Examination Survey (NHANES)**, a nationally representative, cross-sectional datasets. The primary aim is to assess the impact of health and lifestyle behaviors on total cholesterol (TotChol) levels, while specifically examining whether at least one long-term lifestyle behavior modifies the effect of sleep trouble on total cholesterol. The study focused on adults aged 20–59 years with complete measurements for total cholesterol and all selected covariates. Participants with missing or invalid data for key variables were excluded, resulting in a final sample size of n = 2,228.

Variable	Statistic
n	2228
Age	39.43 (11.46)
BMI	28.16 (6.22)
Gender_male	1184 (53.1%)
Race_Black	228 (10.2%)
Race_Hispanic	115 (5.2%)
Race_Mexican	186 (8.3%)
Race_White	1528 (68.6%)
Race_Other	171 (7.7%)
DepressedNone	1777 (79.8%)
DepressedSeveral	321 (14.4%)
DepressedMost	130 (5.8%)
Smoke100_Yes	922 (41.4%)
PhysActiveDays	3.64 (1.81)
SleepTrouble_Yes	550 (24.7%)
Diabetes_Yes	110 (4.9%)
Alcohol12PlusYr_Yes	1906 (85.5%)
RegularMarij_Yes	598 (26.8%)
HardDrugs_Yes	430 (19.3%)
Poverty	3.15 (1.66)

Table 2.1.1: Baseline Descriptive Statistics

2.2. Outcome Variable

The outcome variable in this study is Total Cholesterol (TotChol), a continuous measure reported in mg/dL. Cholesterol is a key biomarker for cardiovascular health, with elevated levels being strongly associated with an increased risk of atherosclerosis and other cardiovascular diseases (Grundy et al., 2004).

2.3. Predictors

2.3.1. Health Factors

Depression (Depressed_cat) is a categorical variable that captures the frequency of self-reported depressive symptoms, categorized as None, Several, Majority, or AlmostAll. Depression is an important predictor due to its well-established associations with dyslipidemia and increased cardiovascular risk (Goldbacher & Matthews, 2007).

Sleep Trouble (SleepTrouble) is a categorical variable (Yes/No) indicating whether participants have reported trouble sleeping to a health professional. Sleep disturbances can disrupt lipid metabolism and contribute to dyslipidemia (Knutson et al., 2007). We use binary sleep trouble rather than continuous sleep duration as the predictor because sleep duration varies by age and does not reliably capture sleep quality.

Diabetes is a categorical variable (Yes/No) indicating whether participants have been diagnosed with diabetes. Diabetes is a known risk factor for dyslipidemia, particularly characterized by low HDL cholesterol and elevated triglycerides(Goldberg, 2001).

2.3.2. Lifestyle Factors

For lifestyle factors, we selected variables that reflected long-term habitual behaviors

based on literature reviews.

Smoking (Smoke100): categorical variable (Yes/No) that reflects whether a participant has smoked at least 100 cigarettes in their lifetime. Smoking is associated with lower HDL cholesterol and elevated total cholesterol (Craig et al., 1989).

Alcohol Consumption(Alcohol12PlusYr): binary variable indicating whether a participant has consumed **at least 12 alcoholic drinks in any one year** (Yes or No), recorded for participants aged 18 years or older. Moderate alcohol consumption is associated with higher HDL cholesterol, whereas excessive intake may have adverse effects (Brien et al., 2011).

Physical Activity (HabitualPhysic): binary variable indicating whether participants engage in physical activity for at least **four or more days per week** (categorized as "Habitual Active") or **less than Four days** ("Less Active"), reported for participants aged **12 years or older**.

Marijuana Use (RegularMarij): binary variable (Yes/No) indicating whether participants have used marijuana regularly. This variable helps us assess whether long-term marijuana use influences cholesterol levels or other health outcomes. (Yankey et al., 2017).

Hard Drug Use (HardDrugs): binary variable (Yes/No) indicating whether participants have used hard drugs, (including cocaine, heroin, methamphetamines.) This variable is important for understanding the health impacts of substance abuse on cardiovascular health, including potential effects on cholesterol metabolism (Racine et al., 2015).

2.3.3. Potential Confounders

Potential confounders include **Age (Age_centered)**, a continuous variable representing the participant's age in years centered around the mean. Age is a critical factor as cholesterol levels typically increase with age (Carroll et al., 2005). **Body Mass Index (BMI_centered)** is another continuous variable, which has been consistently linked to dyslipidemia (Després et al., 2008). **Poverty** (**Poverty_centered)** calculated as the ratio of family income to poverty guidelines and centered around its mean, is included as a potential confounder. Lower socioeconomic status is linked to higher cholesterol levels due to barriers in accessing preventive care and adopting behaviors that regulate cholesterol. Simultaneously, it influences predictors like physical activity and smoking, which are also associated with cholesterol levels (Kaplan et al., 1996). **Gender** and **race** may independently influence cholesterol levels while also being associated with other lifestyle and health factors, necessitating their inclusion to avoid biased estimates (Lemieux et al., 2000) & (Ford et al., 2010).

2.4. Statistical Analysis

This study employed multiple linear regression to examine associations between lifestyle behaviors, health factors, and cholesterol levels, adjusting for potential confounders. Reference cell coding was used to define reference groups for categorical variables. Since the focus is on inference, ensuring unbiased estimators was critical. The Ordinary Least Squares (OLS) estimator from multiple linear regression is the minimum variance unbiased linear estimator among all linear estimators, if Gauss Markov assumptions hold, making it the optimal method for investigating these associations in our research goals. To verify the validity of the OLS

estimator, multicollinearity was assessed using the Variance Inflation Factor (VIF). A VIF greater than 5 indicates the presence of multicollinearity, while values above 10 suggest severe multicollinearity. Forward selection with a significance level of p=0.1 for inclusion was employed to build the main effects model. Model assumptions of linearity, independence, normality, and equal variance (LINE) were evaluated. Linearity was assessed using partial regression plots, while residual versus fitted value plots tested the assumption of equal variance. Independence was assumed due to the cross-sectional nature of the data, with the Durbin-Watson test detecting potential autocorrelation. Although the large sample size of 2,228 minimizes the impact of normality violations on inference, the Shapiro-Wilk test was used to formally assess normality. Interaction terms between long-term lifestyle behaviors and sleep troubles were included to examine effect modification. The extra sum of squares from ANOVA was used to determine whether at least one lifestyle behavior modified the effect of sleep troubles on cholesterol. An influence plot was generated to identify data points with a disproportionate impact on the model.

3. RESULTS

3.1. Evaluation of Multicollinearity

The full model contains all selected predictors and potential confounders. As shown in **Table 3.3.1**, no variable has a Variance Inflation Factor (VIF) greater than 5, indicating that the model does not suffer from severe multicollinearity.

3.2. Model Selection

We used the forward selection method with p=0.1 to identify significant predictors of total cholesterol in the dataset. The stepwise summary **Table 3.2.1** shows the sequential addition of variables based on their statistical significance and improvement in model fit. The forward selection process identifies 11 predictors. **Gender** and **Poverty_centered** are excluded. Since **Gender** and **Poverty_centered** are important confounders related to both cholesterol level and health factors based on literature reviews, we include both in our main effects model.

Stepwise Summary

Step	Variable	AIC	SBC	SBIC	R2	Adj. R2
0	Base Model	6192.766	6204.064	238.642	0.00000	0.00000
1	Age_centered	5976.724	5993.670	22.783	0.09871	0.09828
2	Diabetes	5965.324	5987.919	11.383	0.10445	0.10359
3	HardDrugs	5956.341	5984.585	2.417	0.10912	0.10785
4	Smoke100	5950.703	5984.596	-3.198	0.11236	0.11067
5	RegularMarij	5949.324	5988.865	-4.566	0.11379	0.11167
6	Alcohol12PlusYr	5947.740	5992.930	-6.129	0.11530	0.11276
7	HabitualPhysic	5947.154	5997.993	-6.696	0.11639	0.11343
8	Race1	5945.198	6018.632	-14.564	0.12058	0.11594
9	BMI_centered	5944.962	6024.045	-14.767	0.12151	0.11646
10	Depressed_cat	5945.742	6030.473	-13.961	0.12202	0.11655
11	SleepTrouble	5946.545	6036.925	-13.129	0.12252	0.11663

Table 3.2.1: Stepwise Selection

3.3. Main Effects Model

$$TotChol = \beta_0 + \beta_1(Age\_centered) + \beta_2(BMI\_centered) + \beta_3(Gender) + \beta_4(Race1) + \beta_5(Depressed\_cat) + \beta_6(Smoke100) + \beta_7(SleepTrouble) + \beta_8(HabitualPhysic) + \beta_9(Diabetes) + \beta_{10}(Alcohol12PlusYr) + \beta_{11}(RegularMarij) + \beta_{12}(HardDrugs) + \beta_{13}(Poverty\_centered) + \varepsilon$$

Table: Variance Inflation Factors for Main Effect Model Predictors

Predictor	GVIF	Degrees of Freedom (Df)	Adjusted GVIF ($GVIF^{1/(2\cdot Df)}$)
Age (centered)	1.167	1	1.080
BMI (centered)	1.068	1	1.033
Gender	1.080	1	1.040
Race	1.277	4	1.031
Depression Category	1.076	1	1.038
Smoking History	1.339	1	1.157
Sleep Trouble	1.092	1	1.045
Habitual Physical Activity	1.025	1	1.012
Diabetes	1.067	1	1.033
Alcohol Consumption	1.130	1	1.063
Regular Marijuana Use	1.485	1	1.219
Hard Drug Use	1.365	1	1.168
Poverty (centered)	1.262	1	1.123

Table 3.3.1: The variables in the main effect model exhibit no multicollinearity issues, ensuring that the inference drawn from the model is valid and reliable.

3.4. Model Diagnostics

Linearity is essential in regression to ensure accurate estimates, valid predictions, and reliable inferences. **Figure 3.4.1** shows that **Age_centered, Poverty_centered**, and **BMI_centered** exhibit linear trends suggesting approximate linearity. Scattered residuals indicate potential variability around the fitted lines. Notable outliers (points 1428, 1152) are highlighted.

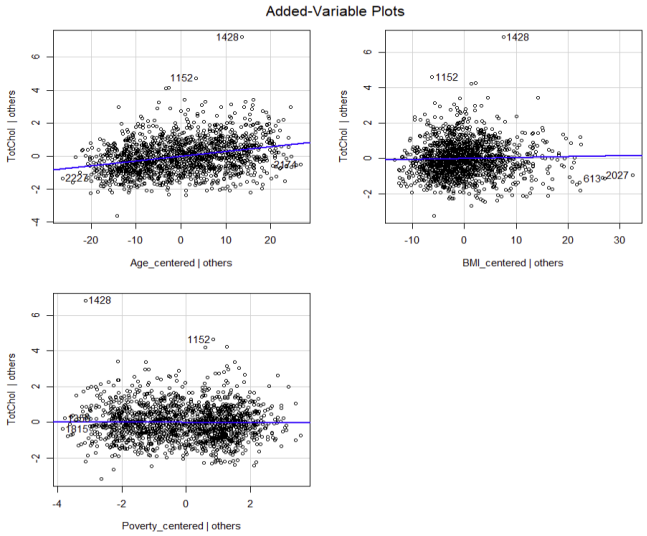

Figure 3.4.1

For equal variance assumptions, we use the residuals vs. fitted value plot to check for homoscedasticity. **Figure 3.4.2** suggests that the residuals are randomly scattered around zero, supporting the assumption of constant variance. Slight variability in spread and the presence of outliers may influence the model. Further investigation of these points is recommended.

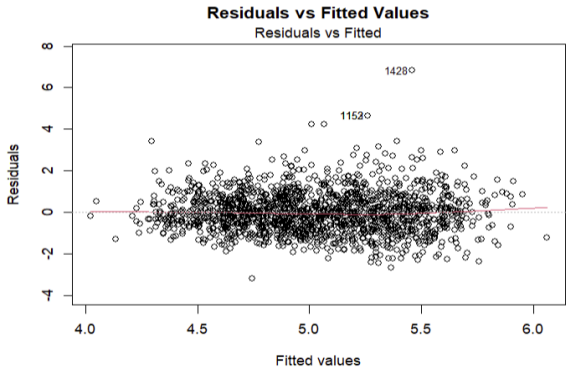

Figure 3.4.2

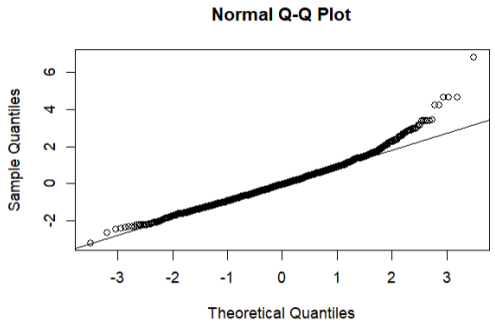

Figure 3.4.3

From **Figure 3.4.3,** the residuals exhibit a generally normal trend; however, there is evidence of a potential deviation characterized by a suspicious right tail. Independence is assumed to hold due to the cross-sectional nature and random sampling of the data. Normality concerns are mitigated by the large sample size (n=2228), ensuring reliable inference.

3.5. Influence Diagnostics

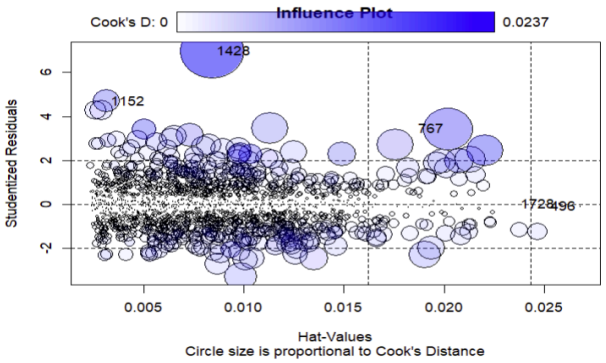

Figure 3.5.1

Influence diagnostic analysis was conducted to identify observations that disproportionately impact the regression model's estimates and overall fit. With prior knowledge highlighting observations 1152 and 1428 as potential targets based on model diagnostics, an influence plot was applied to assess their significance and confirm their influence on the model. From Figure 3.5.1, the point with largest Cook`s D is observation 1428 with highest studentized residuals. Observation 1152 has the second highest residuals value while 767 has relatively large Cook`s D and leverage.

Top 2 Observations with Largest Residuals

Observation	Residual	Leverage	Cooks_Distance	DFFITS
1428	6.821334	0.0084323	0.0237281	0.6423306
1152	4.640863	0.0031509	0.0040607	0.2640656

Table 3.5.2

From **Table 3.5.2,** Observations 1428 and 1152 have the largest residuals.

Top 2 Observations With Largest DFFITS

	Observation	DFFITS
1	1428	0.6423306
2	767	0.4930527

Table 3.5.3

From **Table 3.5.3,** Observation 1428 and 767 have the highest DFFITS.

By analyzing the raw data for these three observations, **Observation 1428** stands out with the highest cholesterol level among them, despite exhibiting no negative lifestyle habits, engaging in regular exercise, and having no health issues. These extreme health-conscious behaviors might explain her large residuals in the model. Both **Observation 1428** and **Observation 767**, despite having completely different lifestyle behaviors, show the highest DFFITS values, suggesting that both extremely healthy and negative lifestyle behaviors may strongly influence the fitted values. Specifically, **Observation 767** has an extremely high BMI well above the average, likely contributing to her status as an influential point and having the second-largest DFFITS value.

3.6. Effect Modification

As sleep was the initial variable of interest for our investigation, all the interaction terms evaluate how various lifestyle factors might affect the relationship between **SleepTrouble** and HDL cholesterol levels. In addition, the variable **HardDrugs** is excluded from the interaction terms because it is a binary variable that only indicates whether a person has ever taken hard drugs, without reflecting long-term usage.

The analysis examined how long-term lifestyle factors influence the effect of sleep troubles on total cholesterol (mg/dL) at a 0.1 significance level, while adjusting for potential confounders and comparing results to the reference group. Habitual physical activity reduced the effect of sleep troubles on total cholesterol by an average of **0.35 mg/dL** compared to individuals without regular physical activity ($p=0.001$). Regular marijuana use reduced the effect of sleep troubles on total cholesterol by an average of **0.21 mg/dL** compared to individuals who did not use marijuana regularly ($p=0.093$). The effect modification between smoking history and sleep troubles ($p=0.7$) and between alcohol consumption and sleep troubles ($p=0.65$) were not significant, with non-smokers and non-drinkers serving as the reference groups.

Among health factors, diabetes was significantly associated with a decrease of **0.41 mg/dL** in cholesterol levels ($p<0.001$), suggesting a potential protective effect. Depression did not show a significant association with cholesterol levels ($p=0.24$). Hard drug use was strongly associated with an increase of **0.26 mg/dL** in cholesterol levels ($p<0.001$), making it the strongest lifestyle factor linked to elevated cholesterol. The extra sum of squares from ANOVA indicates that at least one long-term lifestyle behavior significantly affects the impact of sleep troubles on cholesterol levels ($p=0.09$).

Variable	Estimate	Std. Error	t value	p-value	Significance
(Intercept)	4.977979	0.080080	62.162	< 2e-16	***
Age_centered	0.029225	0.002049	14.260	< 2e-16	***
BMI_centered	0.005762	0.003619	1.592	0.11152	
Genderfemale	0.016086	0.045170	0.356	0.72178	
Race1Black	-0.121092	0.076962	-1.573	0.11578	
Race1Hispanic	-0.220367	0.103341	-2.132	0.03309	*
Race1Mexican	0.029654	0.083362	0.356	0.72208	
Race1Other	-0.174797	0.084485	-2.069	0.03867	*
Depressed_catSeveral	0.073417	0.062739	1.170	0.24206	
Smoke100Yes	-0.123289	0.058181	-2.119	0.03420	*
SleepTroubleYes	0.078005	0.162652	0.480	0.63158	
HabitualPhysicHabitual Active	0.154211	0.050109	3.077	0.00211	**
DiabetesYes	-0.408976	0.102359	-3.995	6.68e-05	***
Alcohol12PlusYrYes	0.076210	0.074013	1.030	0.30328	
RegularMarijYes	-0.045815	0.068245	-0.671	0.50208	
HardDrugsYes	0.259028	0.065229	3.971	7.40e-05	***
Poverty_centered	-0.009605	0.014854	-0.647	0.51795	
Smoke100Yes:SleepTroubleYes	0.045304	0.118448	0.382	0.70214	
SleepTroubleYes:HabitualPhysicHabitual Active	-0.345258	0.105163	-3.283	0.00104	**
SleepTroubleYes:Alcohol12PlusYrYes	0.072059	0.161146	0.447	0.65480	
SleepTroubleYes:RegularMarijYes	-0.213045	0.126832	-1.680	0.09316	.

Table 3.6.1

Model	Residual DF	Residual Sum of Squares (RSS)	Degrees of Freedom (Df)	Sum of Squares (SS)	F-Statistic	p-value	Significance
Reduced	2081	2058.7					
Full	2077	2045.4	4	13.28	3.3712	0.009283	**

Table 3.6.2

4. DISCUSSION

4.1. Limitations and Improvements

This study faced limitations in variable definitions and missing data, which impacted the analysis and its generalizability. **Smoke100** measures lifetime smoking but does not capture current habits or trends, while **Alcohol12PlusYr** lacks detailed patterns of alcohol consumption. Variables like **AlcoholDay** and **AlcoholYear** could offer deeper insights but suffer from high missing rates, reducing the sample size below 800 and introducing bias.

There is a clear trade-off in this study: incorporating potentially better predictors would lead to a more informative analysis, but doing so significantly reduces the sample size and limits overall generalizability. Missing data are particularly concentrated among individuals under 21

and over 59 years, likely due to survey participation differences or reporting biases, further limiting the generalizability of findings.

Future improvements include refining variable definitions to better capture behaviors and trends. Substituting **SmokeNow** for **Smoke100** would reflect current smoking habits, while transforming alcohol-related variables into ordinal or continuous measures could provide a more nuanced understanding. Multiple imputation techniques could address missing data and preserve statistical power. Additionally, transformations of the outcome variable may address normality issues, though further analysis is required to identify appropriate functional forms. For addressing positive correlation, particularly in clustered data, mixed-effects models offer unbiased and efficient estimates by accounting for within-cluster correlations.

From Table 4.1.1, although the assumptions of independence and normality may not have a significant impact on inference given the characteristics of the data, the Durbin-Watson test and Shapiro-Wilk test indicate the presence of positive autocorrelation and that the residuals do not follow a normal distribution.

Durbin-Watson And Shapiro-Wilk Test Results

	Test	Statistic	p-value	Conclusion
1	Durbin-Watson	1.3436	< 2.2e-16	Evidence of positive autocorrelation (reject H0)
2	Shapiro-Wilk	0.97647	< 2.2e-16	Normality assumption violated (reject H0)

Table 4.1.1: Durbin-Watson & Shapiro-Wilk Tests

5. CONCLUSION

The study demonstrates that long-term lifestyle behaviors can influence the relationship between sleep troubles and total cholesterol levels. Habitual physical activity was associated with a notable reduction (**0.35 mg/dL**, p=0.001) in the impact of sleep troubles on cholesterol, and regular marijuana use also appeared to attenuate this relationship (**0.21 mg/dL**, p=0.093). In contrast, no significant effect modification was observed for smoking history or alcohol consumption. Among health factors, diabetes was negatively associated with total cholesterol levels (**−0.41 mg/dL**, p<0.001), while hard drug use was positively associated (**+0.26 mg/dL**, p<0.001). Depression showed no significant association. These findings underscore the importance of considering a range of long-term lifestyle and health factors when assessing the impact of sleep disturbances on cholesterol. They suggest that increasing physical activity and addressing other modifiable behaviors could potentially mitigate the adverse effects of sleep troubles on cholesterol levels.

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