Sweet Dreams: A Regression Analysis of Macronutrient Intake and Sleep Quality

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Group 10: Statistically Speaking

Abstract

Sleep quality is a critical component of overall well-being, with numerous factors affecting its duration and depth. Among these factors, nutrition plays a pivotal yet underexplored role in regulating sleep quality. Accurately measuring an individual's dietary intake is a fundamental challenge in nutritional research. The National Health and Nutrition Examination Survey (NHANES) is an annual survey conducted by the Centers for Disease Control and Prevention (CDC) that collects various health-related data and weights it to be nationally representative. This project takes advantage of the large sample size of the NHANES dataset to draw associations between macronutrient predictors and sleep quality outcomes. Moreover, the demographic data collected through NHANES offers us a way to investigate relevant confounders that are associated with both nutrition and sleep. We identified three final outcome variables related to sleep quality. One outcome was the duration of sleep, rounded to the closest half-hour, on weekdays; this outcome was modeled using multiple linear regression. Another relevant outcome was an indicator for whether the participant had ever told a doctor about trouble sleeping; this was modeled using multinomial regression. The final outcome was a categorical variable asking how often a participant felt overly sleepy during the past month. Furthermore, we aggregated our three sleep outcomes into a single overall metric of sleep quality and fit a Quasi-Poisson regression model. Fiber intake was found to be positively associated with sleep quality, across linear, multinomial, and Quasi-Poisson regressions. Protein was found to have a negative association with length and quality of sleep across the Quasi-Poisson and linear models. Carbohydrates were found to have a harmful effect on sleep quality in the adjusted multinomial models.

Introduction

Although 8 hours of sleep a night is recommended for adults, 37.1% of adults regularly sleep fewer than 7 hours a night (Centers for Disease Control and Prevention, 2011). The effects of poor sleep on health are numerous: those who sleep poorly are associated with having increased

risk-taking behavior, obstructive sleep apnea syndrome (OSAS), cardiovascular disease, a weakened immune system, obesity, diabetes mellitus, migraines, and breast cancer, among other issues (Chattu et al., 2019). Therefore, it is imperative to determine how sleep quality can be improved–macronutrient consumption is one such avenue to explore.

The effect of macronutrient consumption on sleep varies by study. When it comes to sleep latency, some studies have found that high carbohydrate consumption is positively related to sleep onset (Lindseth, Lindseth, & Thompson, 2013; Nehme et al., 2014). Yet others have found no relationship or a negative relationship (Afaghi, O'Connor, & Chow, 2007; Phillips et al., 1975). High carbohydrate consumption has also been shown to be associated with shorter wake times (Lindseth & Murray, 2016). Findings for fat intake are similarly mixed. Some studies have found that a high fat diet is positively associated with improved sleep quality (Irmisch, Schläfke, Gierow, Herpertz, & Richter, 2007; Santana et al., 2012). Another found no relationship (Landström et al., 2000). Yet another study found that dietary fat was associated with worse sleep quality and later sleep onset (Crispim et al., 2011). When it comes to protein, it is known that tryptophan, an amino acid, has a positive impact on sleep because it precedes serotonin and melatonin (Fernstrom, 2013). Decreased tryptophan leads to decreased serotonin, possibly leading to poor sleep (Fernstrom, 2012). Tryptophan cannot be synthesized by the body, and instead protein must be consumed in order to maintain tryptophan levels (*L-tryptophan: MedlinePlus Supplements*, n.d.). Some studies have found that a high protein diet was indeed associated with improved sleep quality (Bravo et al., 2013; Markus et al., 2005). On the other hand, some studies found that a high protein diet was not significantly associated with sleep latency (Adam & Oswald, 1979; Voderholzer et al., 1998).

While carbohydrates, fat, and protein are the three main macronutrients, dietary fiber also appears to be associated with sleep. Dietary fiber is important because when it is metabolized in the colon, the variety and amount of probiotics and short-chain fatty acids increases, which in turn regulate sleep disorders by improving the gut barrier through stimulating the secretion of sleep cytokines, controlling inflammatory pathways, and increasing serotonin secretion (Tang et

al., 2022). One study found that low fiber was associated with lighter, less recuperative sleep and waking up more often during the night (St-Onge et al., 2016).

The aim of this paper is to determine how the macronutrient and fiber composition of one's diet is related to their quality of sleep. Because existing literature has mixed results, this paper will add to the growing body of work that quantifies the relationship between macronutrient consumption and sleep quality.

Research and Analysis Methods

From the NHANES dataset on sleep, we identified four outcomes of interest that we hypothesized would be good proxies for assessing sleep quality. Two of these variables were sleep duration on weekdays and weekends, a self-reported discrete count of hours (rounded to the nearest half hour) that we modeled using multiple linear regression. Another question of the sleep dataset asked participants how often they feel overly sleepy during the day throughout the last month and provided ordinal categorical options from never to almost always. We modeled this outcome using a multinomial regression. The final outcome that we considered was a question that asked participants whether they have ever told a doctor about sleeping troubles. This binary variable was modeled using a logistic regression. The nutritional data for our analysis was sourced from the NHANES dietary survey. This dataset contained a daily account of energy intake in kcal and nutritional intake in grams for all major macronutrient groups. Moreover, this dataset provided weights for each observation that scale the dataset to be nationally representative.

Before proceeding with our analysis, missing data was evaluated. The data that was accessed for this analysis was populated in different data files based on the topic of the survey consisting of demographics, nutrition, and sleep. Merging these datasets posed an early challenge to our work as the sleep dataset was the smallest of the three and therefore any participants missing sleep data would have to be excluded on account of missing the outcome variables. Out of the 6161 respondents of the sleep survey, 333 (5.4%) were not included in the nutritional dataset.

We make the assumption that these participants' exclusion from the dietary dataset is a result of the surveying method. Next, another 564 (9.2%) participants had either not completed the dietary intake survey or did not meet the minimum recall criteria. Our final dataset of complete cases was 5264 participants.

To further investigate the missingness of our data, we developed a new indicator variable that would indicate missingness of sleep outcomes or nutritional predictors for each participant. Fitted logistic models on this missingness outcome were used to identify demographic predictors that had statistically significant associations with missingness. This ruled out the data missing completely at random (MCAR) mechanism, as three demographic variables, US or non-US country of birth, household size and ratio of family income to poverty guidelines, were all statistically associated with data missingness. We proceeded with the assumption that we may be working with a missing not-at-random (MNAR) mechanism. For example, we foresee some participants who already have poor sleep outcomes such as short durations may not have the time to participate in the extensive NHANES surveying and therefore choose to forego certain surveys. Regardless, we decided that in order to proceed with our analysis, we would need to adjust for the three variables listed above.

In the next stage of our analysis, we considered confounding effects in our dataset and identified additional demographic variables to adjust for. We hypothesized that there may be many lifestyle-related variables that would satisfy the classical definition of a confounder—an association with both the exposure and outcome and not a downstream consequence of the exposure. To confirm these associations, we regressed our sleep outcomes and nutritional predictors on various demographic variables. We confirmed that age, sex, race, country of birth, marital status, household size and ratio of household income to poverty guidelines all satisfied the classical confounding definition. Furthermore, we completed operational checks on these confounders by observing the percentage-change in our nutritional predictor slope coefficients after adjusting for a single confounder. For each confounder candidate listed above, the

operational check was satisfied for at least one nutritional predictor, suggesting that these variables can be included in an adjusted model.

A new challenge emerged when incorporating these confounders into our models: while most demographic variables were highly complete with missing answers from just a handful of participants, the marital status and ratio of household income to poverty guidelines did not follow the same trend. Over a third of participants were missing answers to the marital status question and nearly one out of seven were missing answers to the income question. Including these two variables in our models posed a tradeoff: it would adjust for relevant lifestyle factors, but it would also come at the cost of a significant reduction in sample size and downstream power. A decision was made that we would investigate each outcome using three models. The unadjusted models contained exclusively nutritional predictors. The fully-adjusted models contained nutritional predictors and all demographic confounders. Finally, the partially-adjusted models were similar to the fully-adjusted models and also excluded the high-missingness of marital status and income confounders.

Energy (kcal) and sugar were two other predictors that were considered, but were dropped due to multicollinearity. Energy is simply a linear combination of protein, carbohydrates, and fat, while sugar is a subset of carbohydrates.

Because the multinomial and multiple linear regression models explore an individual sleep outcome, we consider a Poisson or Quasi-Poisson regression to combine multiple sleep outcomes into one (Mutiso et al., 2018). Categorical sleep variables SLQ050 and SLQ120 are recoded to binary, where a 1 corresponds to the event that the SP said they've told a doctor they have trouble sleeping and they often or almost always feel overly sleepy during the day (respectively). SLD012 and SLD013 are also recoded to binary: individuals receive a 1 if they have below the mean number of sleep hours of all participants and receive a 0 if they have equal to or above the mean number of sleep hours of all participants, where these thresholds were determined heuristically. The summation of all of these recoded binary variables is assigned to a

new variable sumsleep. Sumsleep can therefore be interpreted as a count of "indicators" of sleep quality, where higher scores correspond to "worse" sleep. While the mean and variance were nearly equal, a Quasi-Poisson was fitted because there was evidence of over-dispersion. There were two adjusted models fitted because of the large amount of missing data within the income and marital status confounders. These Quasi-Poissson models provide estimates for the incidence rate ratios of bad sleep quality indicators in individuals who consume 1 more gram of intake of a given macronutrient per day versus the current grams of intake.

Results and Findings

Multiple Linear Regression

Our first outcome of interest was the average number of hours slept during the weekdays. In NHANES, this data is self-reported and rounded to the nearest half-hour. The average number of hours slept during the weekends was considered, but none of the macronutrients were significantly correlated with this outcome. In the unadjusted model (see Model Statement 1), carbohydrates and fat were not significantly associated with hours of sleep. Protein was significantly associated ($\widehat{\beta}_1$ =-0.0033; p<0.0001); a 20-gram increase in protein is associated, on average, with a 0.0665-hour decrease in sleep (95% CI: -0.0959, -0.0372). Fiber was also significantly associated ($\widehat{\beta}_3$=0.0067; p=0.0076); a 10-gram increase in fiber is associated, on average, with a 0.0671-hour increase in sleep (95% CI: 0.0179, 0.1164). In the fully adjusted model, carbohydrates and fat were again not significantly associated with hours of sleep. Protein was significantly associated ($\widehat{\beta}_1$=-0.0017; p=0.0482); a 20-gram increase in protein is associated, on average, with a 0.0334-hour decrease in sleep (95% CI: -0.0666, -0.0003), holding all other covariates constant. Fiber was also significantly associated ($\widehat{\beta}_3$=0.0082; p=0.0041); a 10-gram increase in fiber is associated, on average, with a 0.0819-hour increase in sleep (95% CI: 0.0261, 0.1378), holding all other covariates constant. In the partially adjusted model, carbohydrates and fat were once more not significantly associated with

hours of sleep. Protein was significantly associated ($\widehat{\beta}_1$=-0.0027; p=0.0005); a 20-gram increase in protein is associated, on average, with a 0.0532-hour decrease in sleep (95% CI: -0.0831, -0.0234), holding all other covariates constant. Fiber was also significantly associated ($\widehat{\beta}_3$=0.0059; p=0.0224); a 10-gram increase in fiber is associated, on average, with a 0.0590-hour increase in sleep (95% CI: 0.008, 0.1100), holding all other covariates constant.

Model Statement 1. Unadjusted multiple linear model regressing average hours slept on weekdays on macronutrients

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 * X_{Proti} + \hat{\beta}_2 * X_{Carbi} + \hat{\beta}_3 * X_{Fibei} + \hat{\beta}_0 * X_{Tfati}$$

Logistic Regression

One of our outcomes of interest came from a question asking participants if they have ever reported sleeping problems to their doctors. As such, this variable is a yes/no indicator variable that follows a Bernoulli distribution with some unknown probability *p*. Under the assumption that *p* shares a linear relationship with our nutrient predictors on the logit scale, our data can be modeled by a logistic regression with Model Statement 2.

Model Statement 2. Unadjusted logistic model regressing indicator of reporting sleeping problems to a doctor on nutrients

$$logit(p) = log(\tfrac{p}{1-p}) = \beta_0 + \beta_1 X_{Prot} + \beta_2 X_{Carb} + \beta_3 X_{Fibe} + \beta_4 X_{Tfat}$$

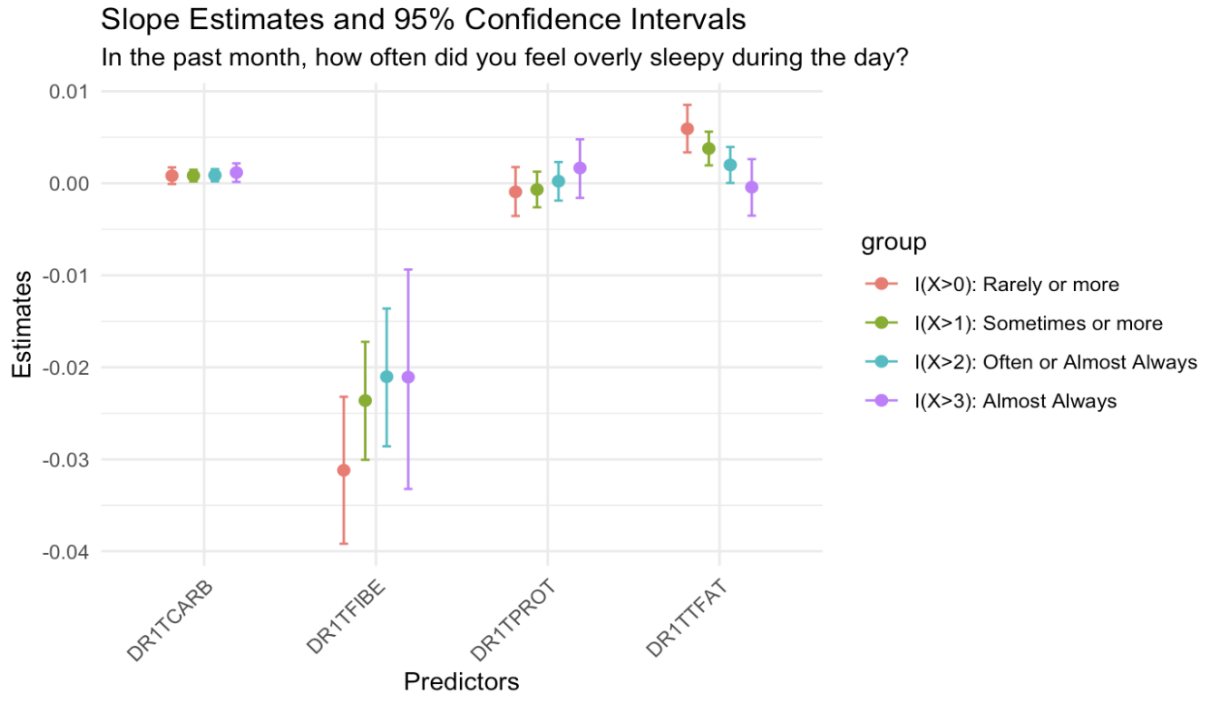
After fitting this unadjusted logistic model, fiber intake and total fat intake were found to be statistically significant. The fitted coefficient for fiber intake was $\widehat{\beta}_3 = 0.0164$ with p = 0.0001 and the fitted coefficient for total fat intake was $\widehat{\beta}_4 = -0.0031$ with p = 0.0021. In the partially adjusted and fully-adjusted models, the total fat predictors lose their statistical significance while the fiber intake variables remain statistically associated with the binary sleep quality outcome. The partially adjusted model has a fitted coefficient for fiber of $\widehat{\beta}_3 = 0.0153$ with a p = 0.0002 and the fully adjusted model has the same coefficient estimated at $\widehat{\beta}_3 = 0.0126$ with a p = 0.0052. As mentioned previously, the partially adjusted model maintains a nice balance of adjusting for some confounders without drastically sacrificing sample size. Using this final model, we can deduce the following interpretation: the group that is 10 grams higher in fiber intake than the current group has an odds ratio of reporting a sleeping issue to a doctor of $e^{10*\widehat{\beta}_3} = 1.1658$ (95% CI: 1.0752, 1.2641).

Multinomial Regression

The final outcome variable in our model was a categorical variable that described the frequency of feeling overly sleepy during the day. This variable had the following coding: 0 = never, 1 = rarely, 2 = sometimes, 3 = often and 4 = almost always. The answer choices for this question possess an inherent ordering about them. To check whether there was any viability in modeling this data through an ordinal-multinomial model, we explore the proportional odds assumption. To confirm whether our predictors maintained proportional odds while moving down the order of the answer choices, we constructed a series of logistic models with indicators at different cutoffs of the order. Using unadjusted models, we then compared the slope estimates and confidence intervals across these different cutoffs. Across all of these models, only the fiber and total fat predictors displayed statistically significant associations with p-values less than 0.05. Figure 1 below shows the slope estimates and their respective 95% confidence intervals for our predictors. It appears as though

there may be a lack of stationarity in odds throughout the answer choice ordering suggesting we should not assume proportional odds.

Figure 1. Proportional Odds Assumption: Comparison of logistic models with moving cutoffs



Seeing as we could not employ the framework of an ordinal regression model, we proceeded with using a multinomial model for this outcome. Under the multinomial model framework, we fit risk ratios for being in certain categories compared to other categories based on predictor inputs. A reference category is used to calculate risk ratios with other categories—in this case the reference is level zero which is the "never" category. We assume that the relationship between risk ratios of the outcome and the predictor variables are linear on the log scale with a model statement as depicted in Model Statement 3 below.

Model Statement 3. Unadjusted multinomial model regressing categories of frequency of feeling overly-sleepy

$$log(\frac{p_1}{p_0}) = \beta_{0,1} + \beta_{1,1}X_{Prot} + \beta_{2,1}X_{Carb} + \beta_{3,1}X_{Fibe} + \beta_{4,1}X_{Tfat}$$

$$log(\frac{p_2}{p_0}) = \beta_{0,2} + \beta_{1,2}X_{Prot} + \beta_{2,2}X_{Carb} + \beta_{3,2}X_{Fibe} + \beta_{4,2}X_{Tfat}$$

$$log(\frac{p_3}{p_0}) = \beta_{0,3} + \beta_{1,3}X_{Prot} + \beta_{2,3}X_{Carb} + \beta_{3,3}X_{Fibe} + \beta_{4,3}X_{Tfat}$$

$$log(\frac{p_4}{p_0}) = \beta_{0,4} + \beta_{1,4}X_{Prot} + \beta_{2,4}X_{Carb} + \beta_{3,4}X_{Fibe} + \beta_{4,4}X_{Tfat}$$

In the unadjusted model, fiber and total fat remained statistically significant across all level comparisons to level zero. For the most extreme comparison, comparing the group of people who almost always get overly-sleepy to the group of people who never get sleepy, the estimated slope of the fiber predictor was $\widehat{\beta}_{3,4}$ = -0.0456 with p = 0.0001. For this same comparison of groups, the estimated slope of the total fat predictor was $\widehat{\beta}_{4,4}$ = 0.0048 with p = 0.0145. When considering the partially adjusted model, fiber remains a statistically significant predictor across all levels of group comparisons. For the same group 4 to group 0 comparison as above, the partially adjusted model has an estimated fiber variable slope of $\widehat{\beta}_{3,4}$ = -0.0364 with p = 0.0001. Interestingly, after partially adjusting for confounders, total fat loses its significant association with the current sleep quality outcome while carbohydrate intake gains a statistically significant relationship. For the same comparison as above, the slope for the carbohydrate predictor is $\widehat{\beta}_{2,4}$ = 0.0023 with p = 0.0007. The fully adjusted model produces similar results to the partially adjusted model. Slope coefficients from multinomial models are estimates of relative risk ratios allowing us to draw associations between our predictors and the categorical outcome. We can interpret that the relative risk ratio of

being in the "almost always" outcome category versus the "never" outcome category is $e^{10*\widehat{\beta}_{3,4}} = 0.7131$ (95% CI: 0.6068, 0.8381) for those that are 10 grams higher in amount of fiber consumed, on average and holding all other covariates fixed. Similarly, the relative risk ratio of being in the "almost always" outcome category versus the "never" outcome category is 1.0235 (95% CI: 1.0099, 1.0372).

Poisson Regression

Table 1. Unadjusted Quasi-Poisson predicting sumsleep summary

Unadjusted Model

	Estimate	exp(Estimate)	exp(10*Estimate)	Std. Error	exp(Std. Error)	P value
(Intercept)	0.4078	1.5036	59.0448	0.0231	1.0234	0.0000
DR1TPROT	0.0006	1.0006	1.0061	0.0003	1.0003	0.0636
DR1TCARB	0.0001	1.0001	1.0008	0.0001	1.0001	0.4275
DR1TFIBE	-0.0059	0.9941	0.9424	0.0012	1.0012	0.0000
DR1TTFAT	0.0009	1.0009	1.0090	0.0003	1.0003	0.0028

Table 2. Adjusted Quasi-Poisson predicting sumsleep with all identified confounders

Model Adjusting for Confounders

	Estimate	exp(Estimate)	exp(10*Estimate)	Std. Error	exp(Std. Error)	P value
(Intercept)	0.3291	1.3897	26.8707	0.0820	1.0855	0.0001
DR1TPROT	0.0008	1.0008	1.0076	0.0004	1.0004	0.0369
DR1TCARB	0.0000	1.0000	1.0004	0.0001	1.0001	0.7364
DR1TFIBE	-0.0055	0.9945	0.9463	0.0013	1.0013	0.0000
DR1TTFAT	0.0005	1.0005	1.0049	0.0003	1.0003	0.1309

Table 3. Partially-Adjusted Quasi-Poisson predicting sumsleep (without marital status and income confounders).

Model Adjusting for Confounders except Marital Status and Income

	Estimate	exp(Estimate)	exp(10*Estimate)	Std. Error	exp(Std. Error)	P value
(Intercept)	0.1942	1.2143	6.9717	0.0603	1.0622	0.0013
DR1TPROT	0.0008	1.0008	1.0081	0.0003	1.0003	0.0150
DR1TCARB	0.0001	1.0001	1.0014	0.0001	1.0001	0.1835
DR1TFIBE	-0.0053	0.9947	0.9487	0.0012	1.0012	0.0000
DR1TTFAT	0.0005	1.0005	1.0048	0.0003	1.0003	0.1157

Tables 1, 2, and 3 show the estimates from the Quasi-Poisson regressions. Across the unadjusted and adjusted models, the estimated coefficient for fiber intake is statistically significant with a p-value < 0.05. Its exponentiated estimate is 0.9947 in the final partially-adjusted model (Table 3). This is the only measured macronutrient with an exponentiated effect estimate < 1 in our Quasi-Poisson. Given this coefficient estimate, we multiply by 10 before exponentiating to achieve a more interpretable incidence rate ratio. We can say that the group that consumes 10 more grams of fiber per day has 0.9487 times the incidence rate of unideal sleep quality indicators as the group at the current level of fiber consumption, on average, and holding all other covariates constant.

Protein intake was not a statistically significant predictor of sumsleep in the unadjusted model, but it was statistically significant in both adjusted models and had an exponentiated effect estimate of 1.0008 in the final partially-adjusted model. Protein is generally a larger part of an individual's diet, so we multiply this coefficient by 20 before exponentiating. We can say that, based on our partially-adjusted model, the group that consumes 20 more grams of protein per day has 1.0163 times the incidence rate of unideal sleep quality indicators as the group at the current level of protein consumption, on average, and holding all other covariates constant.

Carbohydrate and fat intake were found not to be statistically significant predictors of sumsleep in either adjusted model, although the fat intake predictor shows a p-value < 0.05 in the unadjusted model.

Discussion

One limitation of the multiple linear regression models is that all three models have several influential observations. Due to the size of the dataset, it is reasonable for there to be many influential observations, but analyzing every observation for its effect on the regression coefficients was beyond the scope of this project. In order to validate the effects of the macronutrients on hours of sleep, these influential observations must be analyzed.

Another limitation to consider with our modeling is residual confounding. Certain outcomes, such as the question of reporting sleeping issues to a doctor, may be heavily associated with health insurance-related factors. Aspects of this idea are already captured in our adjusted models: the country of birth variable seems to be much more statistically significant for this sleep outcome compared to the others in our analysis. If these factors are not fully captured by the existing demographic confounders, we create the possibility of residual confounding in our models.

The fitted Quasi-Poisson regression has several limitations. The first is its fit to the sumsleep data outcome—there is a steep drop when reaching counts 3 and 4. Furthermore, the relatively small 0 to 4 range of sumsleep may be one source of the overdispersion. Future directions could include incorporating more sleep quality indicators from the other variables in the sleep questionnaire dataset, such as wake-up time, to increase the total range of counts. Further investigation into how each sleep indicator should be defined would also benefit the model.

Conclusion

This paper aimed to determine the association between daily nutritional intake and sleep quality, specifically looking at macronutrients and fiber intake, adding to the existing body of inconclusive research on the relationship between diet and sleep. We found that grams of fiber

intake consistently had a statistically significant and beneficial association with sleep quality, across linear, multinomial, and Quasi-Poisson regressions. Protein was found to have a statistically significant negative association with length and quality of sleep across the Quasi-Poisson and linear models. Carbohydrates were found to have a harmful statistically significant effect on sleep quality in the adjusted multinomial models. While causality remains to be determined, the associations identified here offer insight into the complex relationship between diet and sleep and contribute to the varying conclusions that make up this body of research.

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