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Sleep Quality Predicts Body Shape Index While Adjusting for Physical Activity

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Abstract **Background**: Obesity is a major health problem in the U.S. with prevalence estimated at over 40% in adults. The consequences of obesity are well known and include such health conditions as hypertension, dyslipidemia, hyperglycemia, asthma, arthritis, depression, and poor health-related quality of life. The most common measure used to assess obesity is body mass index (BMI). However, a more recent metric, body shape index (BSI), may provide greater predictive value for the clinical detection of obesity and its connection to chronic disease. Additionally, adequate sleep is currently a popular concern with poor sleep quality (PSQ) seen as a risk factor for many diseases including overweight and obesity. Thus, the aim of this study was to examine the predictive ability of PSQ in estimating BSI while holding physical activity (PA) constant. **Methods**: A cross-sectional convenience sample of 5,945 adults 18+ years of age were used in this study. BSI ($m^{11/6}/kg^{2/3}$) was computed from objectively measured height, weight, and waist circumference (WC). Sleep quality was assessed by a self-report questionnaire with two items asking about sleep time, two items asking about sleep interruptions, one item asking about patient-reported sleep issues, and a final item asking about overall sleepiness. Each sleep quality item was dichotomized to indicate PSQ with six item (PSQ6) (quality and quantity) and four item (PSQ4) (quality only) scores created. Control variables included moderate-to-vigorous PA (MVPA, min/week), sedentary time (ST, min/day), age, sex, race, and income. SAS GLMSELECT was used to predict BSI with PSQ while adjusting for PA and all covariates. **Results**: Approximately 38% of adults had high risk BSI (BSI > .083, $p < .001$) and 42% PSQ (PSQ6 ≥ 2, $p < .001$). BSI was normally distributed (K-S $p > .15$) with mean of .0814 and SD of .0050. Notable bivariate correlations with BSI included PSQ4 ($r = .151$, $p < .001$), PSQ6 ($r = .113$, $p < .001$), MVPA ($r = -.206$, $p < .001$), and age ($r = .569$, $p < .001$). PSQ6 scores predicted BSI ($\beta = 0.0265$, $p = .011$, AIC = -59,790) after adjusting for PA and demographic variables. PSQ4 scores were a stronger predictor of BSI ($\beta = 0.0490$, $p < .001$, AIC = -59,805) after adjusting for covariates. Finally, PSQ status (good vs poor) variables were able to predict BSI where adults with poor PSQ6 and PSQ4 saw significantly ($p < .001$) greater BSI than those with good PSQ6 and PSQ4. **Conclusion**: Results from this study indicate that PSQ is an important predictor of BSI after considering PA. Moreover, quality may be a more important characteristic than quantity when considering poor sleep a risk factor for obesity in adults.

Keywords: *Sleep quality, Body Shape Index (BSI), Physical activity, Population health*

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1. Introduction

The prevalence of obesity in 2020 was estimated at 41.9% among U.S. adults [1]. Such a high rate is a public health concern due to the associations between overweightness and chronic health conditions. Obesity has strong connections to the onset of hypertension, dyslipidemia, hyperglycemia, asthma, arthritis, depression, and poor health-related quality of life, in adult populations [2,3,4,5,6,7,8]. In terms of longevity, obesity is a significant predictor of all-cause, cardiovascular, and cancer-related mortality [9,10,11]. Furthermore, in elderly populations, obesity is associated with various domains of functional disability, including activities of daily living (ADL), instrumental activities of daily living (IADL), leisure and social activities (LSA), lower extremity mobility (LEM), and general physical activities (GPA) [12]. With a growing prevalence of obesity and its unequivocal links to adverse health conditions, many health organizations now label obesity a chronic disease [13].

The prevalence of obesity cited above was assessed using objectively measured height and weight followed by a calculation of body mass index (BMI) [14]. Where BMI values of 30.0 (kg/m^2) and greater indicate obesity [15]. BMI is the most common measure used to classify adults as obese [16]. Despite its widespread adoption in clinical and population-based practices, there are reported validity issues related to the BMI. One criticism for using BMI as an obesity metric is that it does not distinguish between an individual's lean mass and fat mass [17]. For example, an adult with high muscular fitness may have high muscle mass and thus be assessed a high BMI because muscle mass weights more than fat mass. A second criticism for using BMI as an obesity metric is that it does not account for the distribution of body fat [18]. For example, two individuals with the same BMI value could have completely different risk profiles with one having large abdominal fat accumulation and the other a more evenly distributed fat accumulation.

Due to these validity concerns regarding the use of BMI, other metrics have been developed to provide more robust health risk assessments. One such measure is the body shape index (BSI), a measure of waist circumference (WC) that is adjusted for height and weight [19]. The BSI was developed to be a health metric independent of height, weight, and BMI and was initially validated by its strong association with premature mortality [19]. Additionally, BSI has been shown to negatively correlate with lean body mass in adults which is also related to physical activity (PA) [20]. Therefore, the aim of this study was to examine the predictive ability of PSQ in estimating BSI while holding PA constant.

2. Methods

Study design

This study used an observational cross-sectional design that finished data collection in 2020. Participants were recruited across several different demographic characteristics and the sampling scheme should be considered one of convenience. Data were collected from adults 18 years of age and older using self-report questionnaires with body measurements assessed by trained health care professionals [21]. Participants with a BMI $\geq$ 40 kg/m^2 (Class 3 Obese) were excluded from the current study [22].

Body Shape Index (BSI)

BSI was computed with measured study variables of height (cm), weight (kg), and WC (cm). The following formula was used:

$$BSI = \frac{WC}{BMI^{\frac{2}{3}} \times Height^{\frac{1}{2}}}$$

With WC and height converted to units of meters (m) and BMI units of kg/m^2 [19]. BSI units are in m$^{11/6}$/kg$^{2/3}$ as follows:

$$BSI = \frac{WC}{BMI^{\frac{2}{3}} \times Height^{\frac{1}{2}}} = \frac{m}{\left(\frac{kg}{m^2}\right)^{\frac{2}{3}} \times m^{\frac{1}{2}}} = \frac{m}{\frac{kg^{\frac{2}{3}}}{m^{\frac{4}{3}}} \times m^{\frac{1}{2}}}$$

$$= \frac{m}{\frac{kg^{\frac{2}{3}} \times m^{\frac{1}{2}}}{m^{\frac{4}{3}}}} = \frac{m \times m^{\frac{4}{3}}}{kg^{\frac{2}{3}} \times m^{\frac{1}{2}}} = \frac{m^{\frac{7}{3}}}{kg^{\frac{2}{3}} \times m^{\frac{1}{2}}} = \frac{m^{\frac{7}{3}-\frac{1}{2}}}{kg^{\frac{2}{3}}} = \frac{m^{\frac{11}{6}}}{kg^{\frac{2}{3}}}$$

BSI is calculated as a proportion of actual WC (numerator) to the WC expected (denominator) from regression allometry (i.e., body size variables predicting a physical trait) using log height and log weight as predictors of log WC [19]. Regression coefficients are used to form a power function as a more robust representation of the curvilinear relationship. Dividing the power function into the outcome variable, here WC, creates a new ‘scaled’ version of WC. Thus, BSI is a measure of WC adjusted for height and weight (i.e., height and weight removed from WC). BSI will always be positive, have an interpretable mean and SD, and generally range in adults between 0.060 to 0.106 m$^{11/6}$/kg$^{2/3}$. Larger values of BSI indicate a greater health risk associated with WC.

Finally, a BSI risk status variable was created where values greater than 0.083 were considered “high risk” or otherwise “low risk” [23]. Converting BSI to age-and sex-specific standard scores is another approach to creating risk groups – but not implemented in this study.

Sleep Quality (SQ)

Six different participant-reported sleep quality variables were used to create a PSQ scale. Two items asked about usual sleep time, one for weekdays (PSQ_1) and one for weekends (PSQ_2). Both PSQ_1 and PSQ_2 were dichotomized to indicate sleep quality of poor (‘1’) if a participant slept less than 7.0 hours per day. Two items asked about sleep interruptions, one asking how often they snore (PSQ_3) and one asking how often they snort (PSQ_4) while asleep. Both PSQ_3 and PSQ_4 were dichotomized to indicate sleep quality of poor (‘1’) if a participant reported either “occasionally” or “frequently”. One item asked about patient-reported sleep issues (PSQ_5). PSQ_5 was dichotomized to indicate sleep quality of poor (‘1’) if a participant reported that they told a doctor or other health professional that they had trouble sleeping. A final item asked about the frequency of overall sleepiness (PSQ_6). PSQ_6 was dichotomized to indicate sleep quality of poor (‘1’) if a participant reported either “often” or “almost always”.

Since each PSQ item was dummy coded (‘1’ or ‘0’) to indicate poor sleep, summing across the items served as an appropriate PSQ score. Two different scores were computed in this way: 1) a six item (PSQ6: 0 to 6) (quality and quantity) score and 2) a four item (PSQ4: 0 to 4) (quality only) score. Finally, PSQ6 and PSQ4 status variables were created where participants with scores of 2+ were considered having “poor” versus “good” sleep quality.

Physical Activity (PA)

Two different PA variables were used and include sedentary time (ST) and moderate-to-vigorous PA (MVPA) [24,25]. ST was assessed using a single question asking participants how much time they usually spend sitting on a typical day, including school, home, transportation, and work, and excluded sleep. ST units were in minutes per day (min/day). MVPA was assessed from questions that asked participants to exclude work-related and transportation-related PA and to include sport, fitness and recreational activities engaged in for at least 10 minutes continuously. Vigorous-intensity PA (VPA) asked about vigorous-intensity activities that cause large increases in breathing or heart rate and included examples like running or basketball. Moderate-intensity PA (MPA) asked about moderate-intensity activities that cause small increases in breathing or heart rate and included examples like brisk walking, bicycling, swimming, or volleyball. MVPA was computed from both VPA and MPA by adding MPA plus two times VPA and used units of min/week.

Covariates

Demographic covariates of age, sex, race, and income were used in this study. Age was used as a continuous variable, ranging from 18 years to 80+ years. Sex included males and female and dummy coded when appropriate (1=male and 0=female). Race/ethnicity was used as a categorical variable and included White, Black, Hispanic, and Other groupings. Lastly, income was used as a continuous variable and computed as a ratio of the family income to poverty, ranging from 0 to 5.

Statistical analyses

Descriptive statistics were computed to describe the sample and its characteristics. This included percentages and chi-square (χ^2) tests for categorical data and means, standard deviations (SD) and independent t tests for numeric data. Pearson correlations were also computed to examine the bivariate relationships between numeric variables and BSI. Spearman correlations were additionally computed for quasi-interval PSQ score variables and since no differences were noted, only parametric correlations were reported. Normality was assessed for the BSI dependent variable using a histogram, Q-Q plot, descriptive statistics, and the Kolmogorov-Smirnov (K-S) test. BSI was considered normally distributed due to a bell-shaped distribution, linear fitting Q-Q plot, mean of .0814, median of .0814, skewness of 0.0252, kurtosis of 0.0057, and nonsignificant K-S test ($p > .15$).

SAS PROC GLMSELECT was used to perform multiple regression and examine the predictive ability of PSQ for estimating BSI while holding PA constant. All models forced inclusion of MVPA, ST, age, sex, race, and income. Models were compared using the adjusted coefficient of determination ($R^2_{adjusted}$), root mean square error (RMSE), and Akaike information criterion (AIC). Larger values of $R^2_{adjusted}$ and smaller values of RMSE and AIC indicate better relative model fit. Additionally, predicted means, adjusted for all variables, were used to make categorical comparisons of BSI by PSQ status (good vs poor) and sex with effects size (d) statistics included for relative comparisons.

Post model fitting included using PROC REG to examine regression assumptions to ensure that errors were normal, homoscedastic, and independent. Additionally, lack of multicollinearity was assessed using the VIF option with all values less than 2.0. Finally, PROC GLM was used with linear contrasts to examine the validity of PSQ scores as quasi-interval scale. Comparisons were first made between models using the PSQ predictors as quasi-interval versus categorical. In all analyses, the quasi-interval models were preferred due to larger values of R^2 and lower values of RMSE and AIC. Furthermore, since both PSQ4 and PSQ6 scores in categorical models indicated significant ($p < .001$) linear trend, they were also considered adequate quasi-interval linear predictors. All *p*-values were reported as 2-sided and statistical significance set at $p < 0.05$.

3. Results

Table 1 contains the sample characteristics overall and by BSI risk group. Approximately 38.3% of adults had high risk BSI (BSI > .083, $p < .001$) with high proportion disparities seen in male (41.0%, $p < .001$), 65+ year old (72.3%, $p < .001$), white (48.0%, $p < .001$), and low-middle-income (43.4%, $p < .001$) adults. Figure 1 displays the histogram for computed BSI and indicates a normal distribution (K-S $p > .15$) with mean of .0814 and SD of .0050. Table 2 displays descriptive statistics and Pearson correlation coefficients. Approximately 42% and 28% of adults had PSQ as assessed with PSQ6 status ($p < .001$) and PSQ4 status ($p < .001$), respectively. Notable bivariate correlations with BSI include PSQ4 ($r = .151$, $p < .001$), PSQ6 ($r = .113$, $p < .001$), MVPA ($r = -.206$, $p < .001$), and age ($r = .569$, $p < .001$). Additionally, PSQ_1 indicates a negative relationship with BSI and PSQ_2 reveals no relationship with BSI.

Table 1. Sample characteristics overall and by BSI risk

	Overall		BSI Risk (%)		χ^2
Characteristic	*N*	%	Low	High	*p*
Overall	5,945	100	61.8	38.3	<.0001
Sex					<.0001
Female	2,935	49.4	64.6	35.4	
Male	3,010	50.6	59.0	41.0	
Age Group (yr.)					<.0001
18 to 24	745	12.5	92.0	8.1	
25 to 34	920	15.5	85.7	14.4	
35 to 44	897	15.1	77.3	22.7	
45 to 54	907	15.3	65.4	34.6	
55 to 64	1,133	19.1	47.7	52.3	
65+	1,343	22.6	27.7	72.3	
Race					<.0001
White	2,159	36.3	52.0	48.0	
Black	1,432	24.1	71.2	28.8	
Hispanic	1,278	21.5	63.9	36.2	
Other	1,076	18.1	66.3	33.7	
Income Quartile					<.0001
1st (low)	1,486	25.0	62.2	37.8	
2nd (low-middle)	1,485	25.0	56.6	43.4	
3rd (high-middle)	1,488	25.0	63.4	36.6	
4th (high)	1,486	25.0	64.9	35.1	

Note. BSI is body shape index in $m^{11/6}/kg^{2/3}$. BSI risk groups indicate health risk using a cutoff of .083. χ^2 is testing for association between each characteristic and BSI risk group. Participants with BMI > 40 kg/m^2 (class 3 obese) were excluded from the study.

Table 3 shows results from the multiple regression analysis predicting BSI with PSQ6 scores adjusted for control variables. PSQ6 scores were able to significantly predict BSI ($\beta = 0.0265$, $p = .011$, AIC = -59,790) after adjusting for PA and demographic variables. Specifically, for each 1.0 SD increase in PSQ6, mean BSI was estimated to increase by just over .25 SD, indicating a positive relationship between PSQ and BSI. Table 4 shows the same multiple regression analysis but predicting BSI using PSQ4 scores. This model also indicates a significant relationship between PSQ and BSI, however, PSQ4 was able to more strongly predict BSI (ϐ = 0.0490, p < .001, AIC = -59,805) after adjusting for PA and demographic variables. Specifically, for each 1.0 SD increase in PSQ4, mean BSI was estimated to increase by almost .50 SD.

Table 2. Description of quantitative variables (N = 5,945)

Variable	*Mean*	*SD*	*r*	*p*
BSI	0.0814	0.0050	-	-
Sex	0.5063	0.5000	.067	<.0001
Age	48.56	18.38	.569	<.0001
Income	2.65	1.64	-.027	.0376
PSQ4 (0 to 4)	1.06	1.01	.151	<.0001
PSQ6 (0 to 6)	1.45	1.27	.113	<.0001
PSQ_1	0.24	0.43	-.042	.0010
PSQ_2	0.15	0.35	.025	.0522
PSQ_3	0.44	0.50	.134	<.0001
PSQ_4	0.11	0.31	.092	<.0001
PSQ_5	0.26	0.44	.112	<.0001
PSQ_6	0.25	0.43	.019	.1360
PSQ4 status	0.28	0.45	.118	<.0001
PSQ6 status	0.42	0.49	.086	<.0001
MVPA	239.21	513.47	-.206	<.0001
ST	330.28	195.91	.030	.0219

Note. BSI is body shape index in $m^{11/6}/kg^{2/3}$. Pearson correlations (r) are for each variable and BSI. PSQ4 is the 4 item PSQ score. PSQ6 is the 6 item PSQ score. PSQ_1 thru PSQ_6: PSQ6 items dichotomized as 1=poor sleep quality and 0=good sleep quality. PSQ4 status: 1=poor, 0=good. PSQ6 status: 1=poor, 0=good. MVPA is moderate-to-vigorous-PA in min/week. ST is sedentary time in min/day. Sex: 1=male and 0=femal

Table 3. Regression analysis predicting BSI with PSQ6 scores adjusted for demographic and PA variables (N = 5,945)

Parameter	*b*	*B*	*SE*	*t*	*p*
Intercept	0.07586	0	0.000229	331.73	<.0001
Age	0.00015	0.54703	0.000003	50.81	<.0001
Sex					
Female	-0.00055	-0.05502	0.000104	-5.3	<.0001
Male	ref	ref	-	-	-
Race					
White	ref	ref	-	-	-
Black	-0.00228	-0.19442	0.000138	-16.58	<.0001
Hispanic	-0.00054	-0.04393	0.000145	-3.71	.0002
Other	-0.00060	-0.04609	0.000150	-4.01	<.0001
Income	-0.00035	-0.11463	0.000033	-10.61	<.0001
MVPA	0.00000	-0.08924	0.000000	-8.41	<.0001
ST	0.00000	0.04389	0.000000	4.13	<.0001
PSQ6	0.00011	0.02653	0.000041	2.54	.0111

Note. Model $R^2_{adjusted}$ = .374, RMSE = 0.00397, AIC = -59,790.

Table 4. Regression analysis predicting BSI with PSQ4 scores adjusted for demographic and PA variables (N = 5,945)

Parameter	*b*	*B*	*SE*	*t*	*p*
Intercept	0.07579	0	0.000227	333.42	<.0001
Age	0.00015	0.54392	0.000003	50.56	<.0001
Sex					
Female	-0.00056	-0.05539	0.000104	-5.35	<.0001
Male	ref	ref	-	-	-

Parameter	*b*	*B*	*SE*	*t*	*p*
Race					
White	ref	ref	-	-	-
Black	-0.00223	-0.19051	0.000138	-16.24	<.0001
Hispanic	-0.00053	-0.04352	0.000144	-3.68	.0002
Other	-0.00057	-0.04379	0.000150	-3.81	.0001
Income	-0.00035	-0.11374	0.000033	-10.54	<.0001
MVPA	0.00000	-0.08829	0.000000	-8.33	<.0001
ST	0.00000	0.04129	0.000000	3.88	.0001
PSQ4	0.00024	0.04902	0.000052	4.69	<.0001

Note. Model $R^2_{adjusted}$ = .377, RMSE = 0.00396, AIC = -59,805.

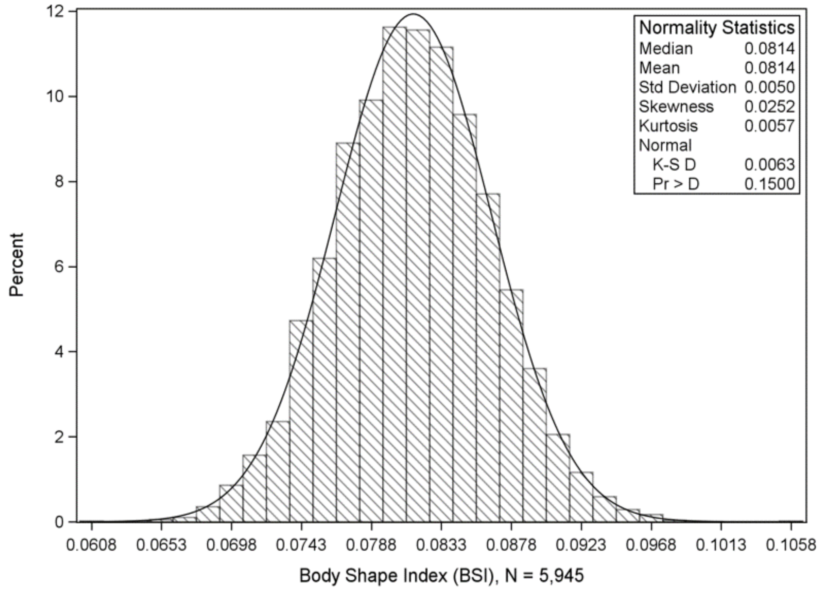

Figure 1. Histogram of computed BSI with normality statistics

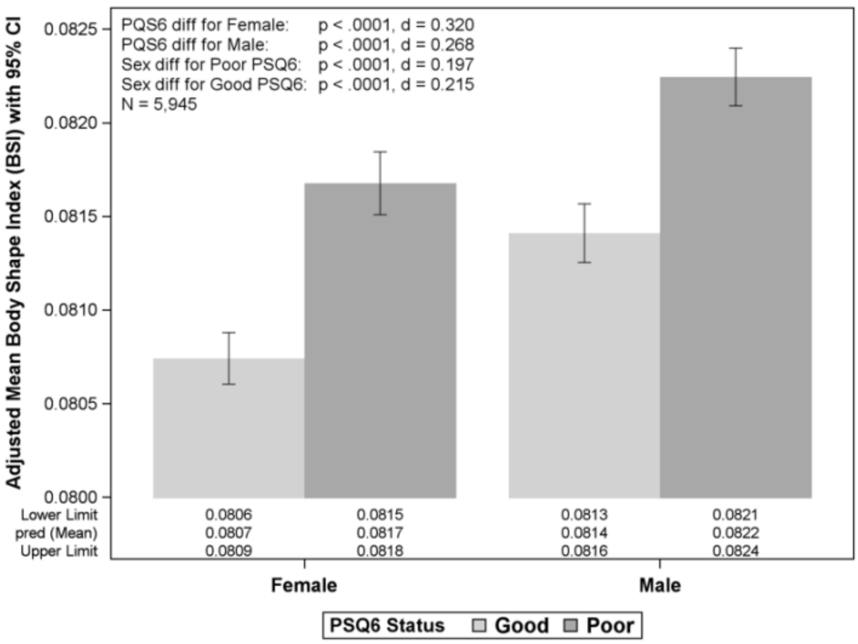

Figure 2. Categorical comparisons of predicted BSI by sex and PSQ6 status.

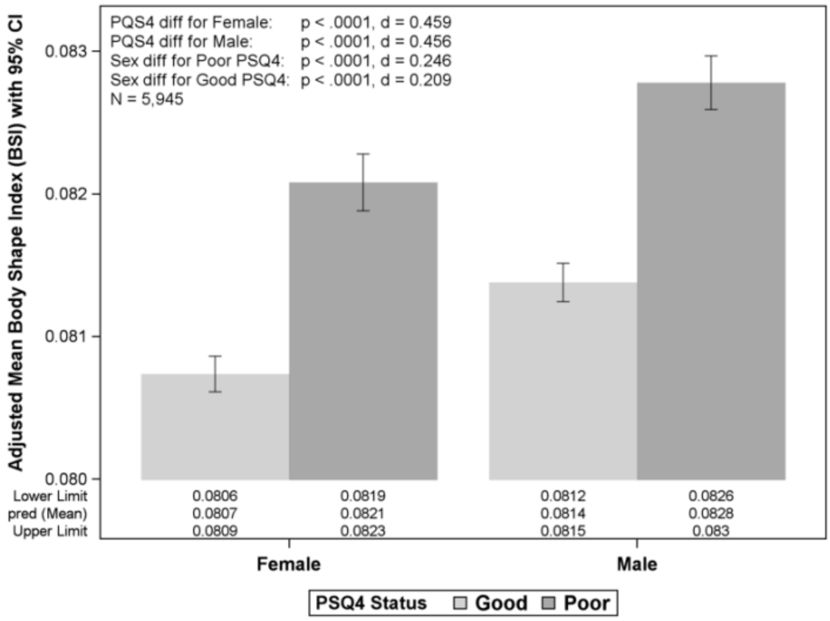

Figure 3. Categorical comparisons of predicted BSI by sex and PSQ4 status

Figure 2 displays categorical comparisons of predicted BSI means by sex and PSQ status (good vs poor), adjusted for all other study variables. The bar graph clearly indicates that PSQ6 status can predict BSI for male (poor: 0.0822 vs good: 0.0814, p < .001, d = 0.268) and female (poor: 0.0817 vs good: 0.0807, p < .001, d = 0.320) adults. Figure 3 displays the same categorical comparisons of predicted BSI means but using PSQ4 status. Similarly, the bar graph shows that PSQ4 status can predict BSI for male (poor: 0.0828 vs good: 0.0814, p < .001, d = 0.456) and female (poor: 0.0821 vs good: 0.0807, p < .001, d = 0.459) adults.

4. Discussion

The purpose of this study was to examine the predictive ability of PSQ in estimating BSI. Additionally, with body composition strongly linked to energy expenditure, the aim included holding PA constant in the modeling process. The findings indicate that both measures of PSQ (PSQ6 and PSQ4) were significant predictors of BSI, controlling for PA. To date, this is the first study to find a relationship between sleep quality and BSI. Using similar body measures, though, evidence does support a sleep quality and body composition relationship. Specifically, PSQ has shown to be a predictor of overweightness and obesity in healthcare professionals [26]. However, this study did not control for PA. In a study of college students, PSQ was associated with both overweightness and obesity, after adjusting for PA and demographic variables [27]. Another study using college students found that sleep disturbance was directly correlated with BMI [28]. However, this study did not control for energy expenditure or activity. Not all studies though have supported the sleep quality and body composition relationship. For example, research of nurses specifically working with covid patients, and experiencing high PSQ (~75%), found no significant relationship between PSQ and BMI [29]. In sum, many studies do corroborate the sleep quality and obesity relationship. However, there are no studies to date showing associations between PSQ and BSI. More research is therefore suggested using BSI as a novel measure of body composition with the addition of also controlling for PA.

Another finding from this study worth noting is the superior predictive power of the four item PSQ (PSQ4) that included only quality-related sleep items. Specifically, the four items assessed snoring, snorting, patient-reported sleep issues, and feelings of sleepiness. Whereas the six item PSQ (PSQ6) included additionally the number of hours of usual sleep for weekdays and the number of hours of usual sleep for weekends. In fact, bivariate analyses indicated that the weekend sleep hours variable (PSQ_2) was not significantly related to BSI and the weekday sleep hours variable (PSQ_1) was negatively related to BSI. Moreover, PSQ4 had a stronger positive Pearson correlation with BSI than PSQ6. Likewise, both sex-specific effect size d statistics were greater in the mean comparison graphs using PSQ4 status than using PSQ6 status. These findings in total may indicate that poor sleep quantity (i.e., less sleep) is associated with lower BSI and thus associated with healthier body composition and may not contribute to a PSQ scale in the way normally hypothesized. More research is needed, however, to further elucidate and support these findings.

Lastly, this study found that categorical status (poor vs good) variables of PSQ were able to predict adjusted BSI scores. A cutoff threshold of one PSQ risk factor was used to indicate good sleep quality. That is, adults suffering either no PSQ risk factors or one PSQ risk factor were considered to have "good" sleep quality and adults reporting two or more risk factors were considered having "poor" sleep quality. The same cutoff rule was used for both PSQ6 and PSQ4 measures. Other published studies have utilized the categorical form of sleep quality in relation to body composition. One study using a large nationally representative sample of adults found an increased odds of being obese among adults with poor sleep quality compared with adults who had good sleep quality [30]. This study, however, only used a single sleep quality item that included responses for self-assessed sleep quality of "very good", "fairly good", "very bad" and "fairly bad". The study did though control for PA along with several other potentially confounding variables. Another study of middle-aged hospital staff found that adults considered to be "good sleepers" had significantly lower BMI than their counterparts considered to be "poor sleepers" [31]. This study used continuous scores from the Pittsburgh Sleep Quality Index before creating a categorical status variable - but did not control for PA. Regardless of these data supporting the use of a categorical sleep quality status variable, further research is needed before standardizing the threshold used in the current research.

One strength regarding this study is its large sample size that provided enough statistical power to support both multivariate regression models [32,33]. Another strength of this study is the sample's diversity across the various demographic characteristics. Specifically, distributions across sex, age group, and race were close to even and should be considered a positive attribute when considering the sampling scheme. A final strength of this study is the fact that body measurements of height, weight, and WC were objectively determined by trained healthcare professionals. Using objectively assessed body measures allows for greater psychometric confidence in the BSI measure, as opposed to self-reported methods [34].

A limitation in this study is its cross-sectional nature which does not allow for cause-and-effect inference. Therefore, findings from this study should only be considered as correlational. Future experimental designs should be conducted to examine the extent to which prior PSQ influences BSI values in adults. Another limitation of this study is its use of a convenience sample. However, despite the bias often associated with samples of convenience, the sample in this study is relatively large and drawn from a wide range of demographic groupings. Therefore, the results from this study could be considered more robust than those from other studies using smaller homogenous samples of convenience. A final limitation of this study is its use of self-reported sleep quality and physical activity. Although self-reported measures have their psychometric drawbacks, the items used in this study are items adopted by large national health surveys [21]. Thus, measurement error may be less than studies using less reliable instruments. In sum, findings from this study should be considered in combination with the above-mentioned limitations.

5. Conclusions

Results from this study have shown that different measures of sleep quality can predict a novel measure of body composition. Specifically, PSQ was found to be an important predictor of BSI after considering PA. Additionally, PSQ status (good vs poor) variables were also able to predict adjusted BSI scores. Finally, it was found that sleep quality may be a more important characteristic than sleep quantity when considering poor sleep as a risk factor for obesity measures in adults.

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