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Development of a Poor Diet Measure and Its Relationship to Physical Activity in High School Students

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Abstract ***Background***: Few studies have used a multi-item approach to measure diet when examining its relationship with physical activity (PA) in youth. ***Design and Methods*****:** Data came from the 2019 Youth Risk Behavior Survey (YRBS). Item response theory (IRT) was applied to develop the Poor Diet Scale (PDS). Ten items were dichotomized to indicate poor diet: fruit juice, fruit, green salad, potatoes, carrots, other vegetables, milk, water, breakfast, and soda. Six variables were dichotomized to indicate PA risk: active for 5+ days (PA5d), active all 7 days (PA7d), 3+ days of muscle strengthening exercise (MSE3d), physical education all 5 days (PE5d), participation in 1+ sport teams (ST1), and combined PA.MSE. Logistic regression was used to model PA using the IRT-derived PDS scores (theta) while controlling for age, sex, race, BMI percentile, and sedentary time. ***Results***: All items significantly fit (*ps* < .001) the IRT model except for soda, which was dropped from the scale. In fully adjusted regression models, odds of PA risk increased significantly (*ps* < .05) with every 1 z-score (theta) increase in poor diet for PA5d (OR = 1.74), PA7d (OR = 1.53), MSE3d (OR = 1.85), PE5d (OR = 1.15), ST1 (OR = 1.73), and PA.MSE (OR = 1.81). Additionally, students not trying to lose weight had significantly (*p* = .004) greater odds as theta increased for PA7d risk (OR = 1.68), as compared to their counterparts (OR = 1.34). ***Conclusions***: Results highlight the utility of using multiple items to measure a complex health risk behavior.

Keywords: *nutrition, diet, physical activity, item response theory (IRT), adolescent health*

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1. Introduction

The prevalence of obesity in the United States (U.S.) has been increasing steadily since 1999 with most recent 2017-2018 figures estimated at 42.4% in adults. [1] Among U.S. youth, ages 2 to 19 years, prevalence of obesity was 18.5% in 2015-2016 and specifically adolescents, ages 12 to 19 years, had the greatest prevalence of 20.6%. [2] The health-related consequences of obesity are well known and include hypertension, dyslipidemia, type 2 diabetes, coronary heart disease, stroke, some cancers, depression, other morbidities, as well as premature mortality. [3,4,5] For adolescent obesity specifically, consequences include psychosocial threats and increased risk of morbidity and mortality carried to adulthood. [6,7,8]

One understood cause of obesity in adolescents is the imbalance between energy intake and energy expenditure. [9] A sedentary lifestyle and lack of physical activity are behaviors related to the energy expenditure side of the energy balance equation. [10] Current U.S. guidelines recommend that all youth engage in 60+ minutes of moderate-to-vigorous PA (MVPA) daily. [11] Additionally, a high quality diet consisting of lower calorie and high nutrient foods is recommended and relates to the other side of the energy balance equation. [12]

One possible reason for the continued growth in adolescent obesity, in light of PA and dietary guidelines, is the lack of understanding regarding how these behaviors relate in adolescent populations. [13,14] Specifically, very few studies analyze the relationship between adolescent PA and a holistic diet measure with established psychometric properties. Instead, many studies on the subject have used single meal, single item, and/or food type frequency items as proxies for diet quality measures. [15,16,17] Additionally, few studies take advantage of the increased psychometric properties provided by using multiple diet-related items to measure a complicated behavioral concept. [18]

Item response theory (IRT) is a modern class of psychometric tools that distinguishes itself from conventional methods by focusing on the items in a test rather than its score. [19] In the behavioral sciences, the items under consideration are each attempting to measure a slightly different aspect of the underlying latent trait.

Additionally, researchers and practitioners use a set of items to assign measurements to individuals that represent how much of this latent trait they possess. In IRT, the latent trait possessed by individuals is referred to as "ability" but can also refer to psychosocial or behavioral concepts such as health-related quality of life, depression, anxiety, and physical activity. An advantage of applying IRT is that it allows for the measurement of individual ability and estimates it on an interval scale with mean of zero, standard deviation of one, and limits of +/- infinity (i.e., a z-score scale). Given that each respondent will be assigned an ability score, referred to as theta (θ), each item can be assessed for functioning by examining the probability of answering the item correctly, referred to as $P(\theta)$. Moreover, if $P(\theta)$ (vertical axis) is plotted against θ (horizontal axis), a sigmoid curve results. By inspecting this curve, referred to as an item characteristic curve (ICC), each item can be assessed for its ability to measure the latent trait.

To date, no studies have used the psychometric capabilities of IRT to develop and assess a diet-related multi-item scale directed toward adolescents. Consequently, no studies have used an IRT-derived diet measure to examine its relationship to PA in adolescents. Therefore, the aim of this study was twofold. Firstly, to develop and validate a scale measuring poor diet in an adolescent population using IRT. Secondly, to examine the relationship between the newly developed Poor Diet Scale (PDS) scores and PA in U.S. adolescents.

2. Design and Methods

Data for this research came from the 2019 Youth Risk Behavior Survey (YRBS), where methodology specifics can be found elsewhere. [20] Briefly, YRBS is a biennial (odd-numbered years) assessment of health-risk behaviors among U.S. high school students. Schools are sampled to represent all U.S. public and private schools and classes are randomly selected from within each school. The instrument is administered in a self-report fashion, contains almost 100 questions, and takes approximately 45 minutes. Survey questions refer to behaviors related to the leading causes of premature death and decreased health status among youth and adults. For example, questions are asked about 1) alcohol, tobacco, and other drug use, 2) physical activity, 3) diet, 4) sexual activity, and 5) behavior leading to unintentional injury and violence. For the 2019 YRBS, 13,677 students provided usable data. Past versions of the YRBS instrument has shown adequate reliability in high school students. [21]

Ten diet variables were used for the PDS development portion of this study. All diet variables concerned the respondent's previous 7 day behavior at the time of reporting. Item names for the diet variables are as follows: *juice*, *fruit*, *salad*, *potatoes*, *carrots*, *vegetables*, *milk*, *water*, *breakfast*, and *soda*. *Juice* represents the drinking of 100% fruit juice, excluding sport and fruit-flavored drinks. Students who reported they did not drink 100% fruit juice were considered at risk and assigned *juice* = 1 and all other students assigned *juice* = 0. *Fruit* represents the consumption of any whole fruit, excluding sport and fruit juice. Students who reported they did not eat fruit were considered at risk and assigned *fruit* = 1 and all other students assigned *fruit* = 0. *Salad* represents the consumption of green salad. Students who reported they did not eat green salad were considered at risk and assigned *salad* = 1 and all other students assigned *salad* = 0. *Potatoes* represents the consumption of potatoes. Students who reported they did not eat potatoes were considered at risk and assigned *potatoes* = 1 and all other students assigned *potatoes* = 0. *Carrots* represents the consumption of carrots. Students who reported they did not eat carrots were considered at risk and assigned *carrots* = 1 and all other students assigned *carrots* = 0. *Vegetables* represents the consumption of all other vegetables. Students who reported they did not eat other vegetables were considered at risk and assigned *vegetables* = 1 and all other students assigned *vegetables* = 0. *Milk* represents the drinking of milk. Students who reported they did not drink milk were considered at risk and assigned *milk* = 1 and all other students assigned *milk* = 0. *Water* represents the drinking of water. Students who reported they did not drink water were considered at risk and assigned *water* = 1 and all other students assigned *water* = 0. *Breakfast* represents eating breakfast. Students who reported they did not eat breakfast were considered at risk and assigned *breakfast* = 1 and all other students assigned *breakfast* = 0. *Soda* represents the drinking of soda or pop, excluding diet soda/pop. Students who reported any amount of soda/pop consumption were considered at risk and assigned *soda* = 1 and all other students assigned *soda* = 0.

Six PA risk variables were created from survey questions and used as main outcomes in the modeling portion of this study. One question asked students how many days they were physically active for 60+ minutes during the past 7 days. From this question, one dichotomous variable was created indicating less than 4 days (PA5d = 1) or 5+ days (PA5d = 0). A second dichotomous variable was created from the same question indicating less than 7 days (PA7d = 1) or all 7 days (PA7d = 0). Another question asked students how many days they did exercise to strengthen or tone their muscles during the past 7 days. From this question, one dichotomous variable was created indicating less than 3 days of muscle strengthening exercise (MSE3d = 1) or 3+ days (MSE3d = 0). One question asked students how many days they attended physical education class during an average school week. From this question, one dichotomous variable was created indicating less than 5 days (PE5d = 1) or all 5 days (PE5d = 0). Another question asked students how many sport teams they played on during the past 12 months. From this question, one dichotomous variable was created indicating 0 sport teams (ST1 = 1) or 1+ sport teams (ST1 = 0). A final composite dichotomous PA variable was created indicating not meeting both the 7 days of PA and the 3+ days of muscle strengthening exercise (PA.MSE = 1) or meeting one or both (PA.MSE = 0).

Five different control variables were used in the modeling portion of this study and included student age, sex, race/ethnicity, body mass index (BMI) percentile, and sedentary time. Student age was assessed from a survey question and took on seven discrete values ranging from 12 to 18+ years of age. Student sex was categorical representing either male or female. Student race/ethnicity was categorical with students classified into collapsed groups of either White, Black, Hispanic, or Other. BMI percentile was used as a numeric variable where BMI (kg/m^2) was first computed from reported weight and height followed by the computation of an age and sex-specific percentile for each student. A sedentary time variable was also constructed from responses to two questions regarding the average hours per day watching TV and average hours per day playing video/computer games. Both the TV and video/computer questions had a 7 ordinal category response ranging from 0 to 5+ hours per day and therefore the combined (summed) sedentary time variable was considered numeric and ranged from 0 to 14 where 14 indicated the most sedentary. Finally, for moderation effect analysis, a trying to lose weight (TLW) variable was used. TLW was formed from a question asking students if they were: trying to lose weight, gain weight, stay the same weight, or none of the above. From this question, one dichotomous variable was created indicating trying to lose weight (TLW = 1) or not trying to lose weight (TLW = 0).

Expanding on the above introduction, the ICC is a tool of focus in an IRT analysis. [19,22] The ICC has the interval scale measured trait, theta (θ), on the horizontal axis and the probability of correctly responding to the item, $P(\theta)$, on the vertical axis. (Although IRT models and ICCs are available for polytomous items, only dichotomous IRT models and ICCs will be discussed here). The ICC is depicted by a sigmoid curve, where the probability of a correct response is low at lower ability (theta) levels and high at higher ability levels. For a math ability test item scored correct or incorrect, this curve is intuitive. For a dichotomous psychosocial item, responding correctly to the item is considered "endorsing" the item and also has an ICC with a sigmoid curve. The two more common item characteristics (parameters) inspected in an ICC are its *difficulty* and its *discrimination*. An item's difficulty parameter (b) measures how difficult it is to endorse and from the ICC is depicted by the location of the curve on the theta axis. Specifically, item difficulty is a value of theta when $P(\theta) = 0.50$ and item curves shifted to the right are considered more difficult than item curves at the left. An item's discrimination parameter (a) measures how well the item can differentiate respondents in terms of theta. From the ICC, the item discrimination is depicted from the steepness of the curve (i.e., rate of $P(\theta)$ change per change in theta) near its difficulty value and therefore is sometimes referred to as item slope. Thus, an item is discriminating at its best at and around its difficulty parameter value.

Since this study examined dichotomous response psychosocial items, three appropriate IRT models were considered: 1) one-parameter logistic (1PL) model, 2) Rasch model, and 3) two-parameter logistic (2PL) model. A brief description of each model will be given with detailed discussion found elsewhere. [23] An IRT model entails a mathematical relationship between the probability of endorsing an item and individual ability while considering either one or two item parameters previously mentioned. The 1PL model is a cumulative logistic function with a difficulty (b) parameter for each item and a fixed value of discrimination (a_{fixed}). The 1PL model has the following form:

$$P(\theta) = \frac{1}{1 + e^{-a_{fixed}(\theta - b)}}.$$

Although the 1PL model contains a fixed value for a, this is not considered a model parameter. Hence, the 1PL model contains the b parameter only. The Rasch model is mathematically equivalent to the 1PL model, and sometimes referred to as such, but differs with a fixed value of $a = 1.0$. The Rasch model has the following form:

$$P(\theta) = \frac{1}{1 + e^{-1.0(\theta - b)}}.$$

The Rasch model also differs philosophically from the 1PL model as a preferred model for measurement development. [24] This difference will only be discussed if these two models are considered the better fitting models in this study. Finally, the 2PL model includes both item parameters previously discussed and has the following form:

$$P(\theta) = \frac{1}{1 + e^{-a(\theta - b)}}.$$

The 2PL model has both a difficulty (b) and discrimination (a) parameter. To illustrate, a person with an ability of $\theta = 1.5$ responding to an item with parameters of $b = 1.0$ and $a = 0.75$ would have a $P(\theta) = 0.59$, under the 2PL model,

$$P(\theta) = \frac{1}{1 + e^{-0.75(1.5 - 1.0)}} = 0.59.$$

At this ability level, which is greater than the item's difficulty parameter, the respondent has a greater chance of endorsing the item, as compared to a person with a lower ability level (e.g., a person with an ability of $\theta = 1.0$ would have a $P(\theta) = 0.50$ for the same item).

Statistical analyses were separated into two different stages: 1) a PDS development stage, and 2) a PDS score and PA relationship modeling stage. For the scale development stage, each of the three above-mentioned IRT models were run and examined for fit. Three typical statistics were examined for model comparison and included the likelihood ratio test statistic (G^2), Akaike's information criterion (AIC), and Bayesian information criterion (BIC). After selecting the best fitting IRT model, items were evaluated for their fit. Item fit was assessed using the G^2 and the magnitude of the slope (a) parameter (as > .34 were acceptable). [19,25] All included scale items were then assessed further by evaluating item-total correlations, item-to-item tetrachoric correlations, and scale reliability using the ordinal alpha method. [26] Adequate item-total correlations should exceed .50, item-to-item correlations should exceed .30, and the internal consistency reliability coefficient should have a lower limit of .70. [27] For the PDS score and PA relationship modeling stage, diet and PA risk behavior percentages were computed and sex differences tested using the chi-square test of independence. Logistic regression models were then run using the newly

IRT-derived PDS scores (theta, θ) as the independent variable with separate models for each PA outcome variable. Regression models were run both unadjusted (PDS score predicting PA risk) as well as adjusted for age, sex, race, BMI percentile, and sedentary time. Finally, the moderating effect of TLW on the diet and PA relationship was evaluated by testing the theta × TLW interaction in all PA outcome models. SAS version 9.4 was used for all analyses. [28]

3. Results

A total of N = 8,270 high school students had complete diet data for the first stage of the study. Table 1 contains model comparison statistics for the three IRT analyses. The 2PL model showed a significantly better fit to the data as seen by the likelihood ratio test (G^2_{Change} = 1,817, p < .001). Additionally, *AIC* and *BIC* statistics supported the 2PL, indicating the extra parameters were worth estimating. Therefore, all continuing model fitting steps were on the 2PL IRT model. Table 2 contains item parameter estimates and fit statistics for the final PDS. One item, Soda, was removed from the scale due to a slope (a) parameter of zero. Thus, nine significant (ps < .001) fitting items comprised the PDS. Item difficulty (b) ranged from -0.13 to 2.62, indicating items target easy to very difficult in terms of the poor diet behavior trait required to endorse them. Item discrimination (a) ranged from 0.53 to 2.39, indicating items ranged from low to very high in their ability to detect small changes in poor diet trait. Table 3 contains classical means of validating the PDS post-hoc. Ordinal alpha, for scale reliability, indicates acceptable (α > .70) internal consistency (α = .793) for the PDS. Furthermore, most item-total correlations approached or exceeded the acceptable cutoff (i.e., .50) and several item-to-item correlations approached or exceeded acceptable cutoff (i.e., .30) for the PDS.

Table 1. Model comparison statistics

Statistic	1PL	Rasch	2PL
AIC	85106	85106	83307
BIC	85183	85183	83447
LL	-42542	-42542	-41633
df	1012	1012	1003
G^2_{Change}		1817	
df_{Change}		9	
p		<.001	

Note. N = 8,270 for all models. 1P is the 1-parameter IRT model with equal slope parameter. Rasch is the Rasch model with slope parameter set to 1.0. 2P is the 2-parameter IRT model. LL is the log likelihood. G^2_{Change} is the likelihood ratio test statistic. *AIC* is Akaike's information criterion (lower is better). *BIC* is Bayesian information criterion (lower is better). All models in this table used the 10 initial poor diet dichotomous items.

Table 2. Item parameter estimates and fit statistics for 2PL IRT model of the Poor Diet Scale (PDS)

Item	Difficulty (b)	Discrimination (a)	a Interpretation	G^2	p
Juice	1.605	0.542	Low	734.14	< .001
Fruit	1.764	1.680	High	238.24	< .001
Salad	0.320	1.362	High	1073.00	< .001
Potatoes	0.796	0.852	Moderate	853.86	< .001
Carrots	-0.135	1.441	High	2188.00	< .001
Vegetables	1.083	2.389	Very high	881.82	< .001
Milk	1.634	0.527	Low	694.46	< .001
Breakfast	2.546	0.691	Moderate	544.65	< .001
Water	2.616	1.706	Very high	66.72	< .001

Note. N = 8,270. Item difficulty range: -0.13 to 2.62. Item discrimination range: 0.53 to 2.39. a interpretation column from Baker and Kim, 2017 [19]. Soda was removed from the scale because of a zero slope (discrimination). G^2 is the likelihood ratio test statistic proposed by McKinley and Mills, 1985 [25].

Table 3. Poor Diet Scale (PDS) statistics

	Difficulty		Item-Total	Tetrachoric Correlation Matrix (α = .793)							
Item	Mean	SD	Correlation	Fruit	Salad	Potatoes	Carrots	Veggies	Milk	Breakfast	Water
Juice	0.31	0.46	.448	.333	.145	.205	.144	.193	.244	.157	.277
Fruit	0.11	0.31	.500		.464	.257	.405	.519	.192	.327	.551
Salad	0.42	0.49	.566			.293	.440	.525	.090	.170	.281
Potatoes	0.36	0.48	.514				.278	.388	.171	.159	.276
Carrots	0.53	0.50	.568					.552	.180	.161	.302
Vegetables	0.19	0.39	.594						.216	.274	.544
Milk	0.31	0.46	.443							.246	.354
Breakfast	0.17	0.37	.405								.452
Water	0.04	0.19	.365								

Note. N = 8,270. Items dichotomized as 1 = poor diet and 0 otherwise. Scale reliability, α = .793, is ordinal alpha. Correlation between Poor Diet IRT-derived Theta and Poor Diet Scale (PDS) sum score is r = .955, p < .001. Theta values computed using maximum a posteriori method.

Table 4. Diet and physical activity (PA) risk behavior percentages in U.S. high school students, YRBS 2019

	Overall		Female		Male		χ^2
Behavior	*N*	%	*N*	%	*N*	%	*p*
Diet Risk							
Juice	2,533	30.7	1,440	33.9	1,079	27.5	< .001
Fruit	913	11.2	383	9.5	523	12.9	< .001
Salad	3,466	41.5	1,590	36.8	1,850	46.1	< .001
Potatoes	2,951	35.0	1,573	36.0	1,349	33.9	.142
Carrots	4,419	52.7	2,279	54.4	2,108	51.0	.079
Vegetables	1,563	19.3	745	18.4	806	20.3	.120
Milk	2,544	30.4	1,651	39.6	875	21.4	< .001
Breakfast	1,378	16.6	679	16.6	684	16.6	.973
Water	307	3.7	102	2.3	203	5.1	< .001
PA Risk							
PA5d	4,479	53.8	2,618	62.9	1,831	44.9	< .001
PA7d	6,266	75.5	3,500	83.8	2,722	67.3	< .001
MSE3d	4,227	50.7	2,553	60.3	1,644	41.3	< .001
PE5d	5,995	72.2	3,209	75.7	2,747	68.8	< .001
ST1	3,455	42.1	1,851	45.1	1,576	39.1	< .001
PA.MSE	3,854	46.4	2,382	56.7	1,445	36.3	< .001

Note. Estimates are among those with complete diet data and do not represent national prevalence estimates. χ^2 test is for sex differences. Juice = Indicating did not drink fruit juice past 7 days. Fruit = Indicating did not eat fruit past 7 days. Salad = Indicating did not eat salad past 7 days. Potatoes = Indicating did not eat potatoes past 7 days. Carrots = Indicating did not eat carrots past 7 days. Vegetables = Indicating did not eat other vegetables past 7 days. Milk = Indicating did not drink milk past 7 days. Breakfast = Indicating did not eat breakfast past 7 days. Water = Indicating did not drink bottle/glass of plain water past 7 days. Soda = Indicating did drink soda past 7 days. PA5d = Indicating was not physically active for 60+ min per day for 5+ days. PA7d = Indicating was not physically active for 60+ min per day on all 7 days. MSE3d = Indicating did not engage in muscle strengthening exercise for 3+ days. PE5d = Indicating did not attend physical education classes on all 5 days. ST1 = Indicating did not play on at least one sport team. PA.MSE = Indicating did not meet both PA7d and MSE3d.

Table 5. Logistic regression results predicting different forms of physical activity (PA) risk from IRT-derived Poor Diet Scale (PDS) scores (theta, θ) in U.S. high school students, YRBS 2019

	Unadjusted				Adjusted			
Outcome	N	OR	LL	UL	N	OR	LL	UL
PA5d	8,232				7,211			
Theta (θ)		1.76	1.63	1.90		1.74	1.60	1.90
PA7d	8,232				7,211			
Theta (θ)		1.54	1.40	1.70		1.53	1.41	1.67
MSE3d	8,222				7,208			
Theta (θ)		1.85	1.71	2.00		1.85	1.71	2.00
PE5d	8,185				7,177			
Theta (θ)		1.16	1.02	1.31		1.15	1.01	1.30
ST1	8,194				7,183			
Theta (θ)		1.76	1.65	1.88		1.73	1.61	1.86
PA.MSE	8,210				7,204			
Theta (θ)		1.81	1.67	1.95		1.81	1.67	1.96

Note. Each regression analysis is modeling PA risk. OR is odds ratio. LL and UL are the lower and upper limits (respectively) of the 95% confidence interval. Theta (θ) is the IRT-derived poor diet score and has values like z-scores. PA5d = Indicating was not physically active for 60+ min per day for 5+ days. PA7d = Indicating was not physically active for 60+ min per day on all 7 days. MSE3d = Indicating did not engage in muscle strengthening exercise for 3+ days. PE5d = Indicating did not attend physical education classes on all 5 days. ST1 = Indicating did not play on at least one sport team. PA.MSE = Indicating did not meet both PA7d and MSE3d. Adjusted models are adjusted for age, sex, race, BMI percentile, and sedentary time.

Table 6. Logistic regression results predicting physical activity (PA) guidelines risk (PA7d) from IRT-derived Poor Diet Scale (PDS) scores (theta, θ) in U.S. high school students, YRBS 2019

		Were trying to lose weight (TLW)					
	Interaction	Yes (*N*=3,737)			No (*N*=3,446)		
Outcome	*p*	OR	LL	UL	OR	LL	UL
PA7d							
Theta (θ)		1.34	1.18	1.52	1.68	1.51	1.87
Theta × TLW	.004						

Note. OR is odds ratio. LL and UL are the lower and upper limits (respectively) of the 95% confidence interval. Theta (θ) is the IRT-derived poor diet score and has values like z-scores. PA7d = Indicating was not physically active for 60+ min per day on all 7 days. TLW = Trying to lose weight. Models are adjusted for age, sex, race, BMI percentile, and sedentary time.

Table 4 contains percentages of diet-related and PA-related risk behaviors in high school students. Poor diet behaviors with the overall highest rates were Carrots (52.7%), Salad (41.5%), and Potatoes (35.0%) and those with the overall lowest rates were Water (3.7%), Fruit (11.2%), and Breakfast (16.6%). Males were at greater risk for poor diet with Fruit, Salad, and Water (*ps* < .001). Whereas females were at greater risk for poor diet with Juice and Milk (*ps* < .001). PA risk was greatest overall for PA7d (75.5%) and PE5d (72.2%), with females at greater risk for all PA variables (*ps* < .001). Table 5 displays results for the logistic regression models predicting PA risk using the IRT-derived PDS scores (theta, θ). PDS scores resemble standard (*z*) scores and therefore a 1-unit change in PDS score represents a 1 *z*-score change. The PDS score significantly predicted PA risk in all models, unadjusted and adjusted. PDS scores had the smallest effect on PE5d, with an (adjusted) increased odds of only 1.15 (95% CI: 1.01 – 1.30) for each unit increase in PDS score. In other words, as poor diet behavior increased by 1 unit, the odds of not attending physical education class on all 5 days of the school week increased by 15%. PDS scores had the largest effect on MSE3d, with an (adjusted) increased odds of 1.85 (95% CI: 1.71 – 2.00) for each unit increase in PDS score. Said differently, as poor diet behavior increased by 1 unit, the odds of not engaging in muscle strengthening exercise 3+ days a week increased by 85%. Finally, Table 6 contains results for the moderation analysis. Specifically, this analysis examines the extent to which TLW changes the PDS score and PA relationship. Of the six PA models, TLW only significantly (*p* = .004) moderated PA7d, with increased odds of 1.68 (95% CI: 1.51 – 1.87) and 1.34 (95% CI: 1.18 – 1.52), for those not TLW and those TLW, respectively.

4. Discussion

This study utilized a novel approach in developing and validating a new poor diet score in high school students. Specifically, a 2PL IRT model was used to present psychometric evidence supporting the nine-item PDS. Results of the IRT analysis indicated the PDS targets a moderately wide range of poor diet trait with adequate discriminating properties. Furthermore, classical post-hoc procedures confirmed reliability of the newly developed PDS. To highlight, the measurement portion of this study is novel for three primary reasons. First, this is the first study to develop and validate a brief, self-report, multi-item scale measuring poor diet behavior in high school students. Currently, if a researcher wants to assess the diet quality of a large group of high school students, they would likely resort to administering either a Food Frequency Questionnaire (FFQ) or the Healthy Eating Index (HEI). [29,30] However, these assessments are long, cause undue burden on the participants, and can be difficult to score. [31] Therefore, a validated nine-item self-report tool, with items found in most school-based health surveys, can benefit health behavior researchers. Second, the psychometric properties of the IRT-developed PDS are considered both item and sample invariant. [32] That is, a high school student should receive the same PDS score regardless of which diet items they are administered and the PDS items should have the same difficulty and discrimination regardless of who is in the sample. Third, the IRT-derived ability scores (theta) possess an interval-scale property. This IRT scoring characteristic allows for a more accurate use of the PDS scores, such as their use in advanced statistical modeling.

This study also used the IRT-derived PDS scores to examine the extent to which poor diet relates to PA risk in U.S. high school students. Findings consistently showed that poor diet relates to all forms of PA risk assessed in this study. That is. students with higher poor diet scores had even greater odds of PA risk, as seen in all six PA risk variables (PA5d, PA7d, MSE3d, PE5d, ST1, and PA.MSE). These findings are noteworthy for three reasons. First, showing that poor diet behavior was associated with five different PA outcome variables (and an additional constructed variable) provides more robust findings supporting this relationship. Other studies have examined this relationship in youth, with null results, but using only a single PA measure. [33,34] A few recent studies have shown such a relationship in school-aged children, however, when adherence to the Mediterranean diet was examined in association with exercise frequency and PA. [35,36] These findings support the current study findings, albeit, using a different diet measure, a single PA measure, and a younger population (ages 8 to 13 years) from Spain. Second, this study also used a novel predictor variable in its modeling of PA risk. That is, the IRT-developed measure of poor diet behavior was able to utilize information from several different diet items to create a single score. Furthermore, the PDS score can be considered an accurate and efficient one because items were only included if they were able to discriminate between individuals on the poor diet latent trait. Research in the areas of health literacy, healthcare quality, cardiometabolic risk, and quality of life have used IRT in a similar way as the current study. [37,38,39] However, no studies to date have used IRT to score a diet-related scale and subsequently use those scores to model PA. Third, no studies to date have examined the moderating effect that weight management goals, such as TLW, have on the poor diet and PA relationship in U.S. high school students. One recent study of teenagers showed that those attempting to lose weight were more likely to skip breakfast and eat some healthy food items. [40] However, this study found no significant association between teenagers attempting to lose weight and their PA and the diet and PA relationship was not examined across weight management goal groups.

Although this study incorporated some innovative methods in examining the relationship between diet and PA in U.S. high school students, some limitations should be noted. Firstly, results from this study represent a cross-sectional analysis of students attending high school. Therefore, this study was unable to show that poor diet causes PA risk and this study was unable to generalize to students not attending a public or private high school. Secondly, all PA variables in this study were assessed using self-reported survey items. Objectively measured PA or longer scales with superior psychometric properties may improve PA risk classification. Thirdly, diet items administered to students in the YRBS assessed the frequency of food intake and not portion size and therefore some misclassification may be present in the poor diet item dichotomization. Given these stated limitations, inferences from this study should be viewed with caution.

In conclusion, this study presents robust findings supporting the relationship between diet and PA in U.S. high school students. Specifically, a continuous measure of poor diet was directly related to PA risk when assessed using weekly PA, physical education class attendance, muscle strengthening activity, and participation in team sports. This relationship was stronger among students not TLW, as compared to those TLW. Results also highlight the utility of using multiple items to measure a complex health risk behavior. Health promotion specialists should focus on the diet and PA relationship when designing program involving high school students.

Significance for Public Health

Obesity has become a global health problem, which in the United States (U.S.) has increased steadily in past decades. Obesity is related to several health conditions during adolescence as well as diseases carried to adulthood. Diet and physical activity (PA) are two behaviors known to prevent and combat obesity in youth and therefore knowledge of their relationship is integral to public health. Results from this study should inform health promotion professionals on the impact that diet has on PA in high school students.

Ethical Approval

Not required for the current study.

Availability of Data and Material

Data used in this study are available from U.S. CDC, https://www.cdc.gov/healthyyouth/data/yrbs/index.htm.

Disclosure

The authors have no conflict of interest to declare.

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