Published in final edited form as:

J Nutr Educ Behav. 2015 ; 47(3): 253–258. doi:10.1016/j.jneb.2014.12.005.

Four Dietary Subscales of the SPAN Questionnaire Form a Robust Latent Variable Measuring Healthy Eating Patterns

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Abstract

Objective—Evaluating the factor structure of four dietary subscales (Fruits, Fruit Juice, Vegetables, and Milk) from the School Physical Activity and Nutrition (SPAN) questionnaire elementary version.

Methods—Secondary analysis of intervention data from 3rd grade classrooms measured at pre-intervention, post-intervention (10 weeks), and three month follow-up. SEM invariance analysis was conducted to test the stability of the factor structure of the four subscales.

Results—1,147 students participated. Fit indices revealed good fit for a single factor remaining stable across time (χ^2 [df = 59] = 59.75), across gender (χ^2 [df = 128] = 149.72), and across study group (χ^2 [df = 128] = 143.04).

Conclusions and implications—A *Healthy Food* factor consisting of the four subscales can be used in future data analysis. This offers several advantages in analysis, including the use of latent change scores that are more powerful, more informative, and more easily interpreted than traditional approaches.

Keywords

Child; Diet; Nutrition Assessment

Childhood obesity has risen substantially during the last few decades.¹ Monitoring children's health behaviors can help to determine the correlates and causes of weight gain.² This is particularly important for diet, as dietary patterns often extend into adolescence and adulthood, and dietary intake has been linked to childhood obesity.^{3,4} The School Physical Activity and Nutrition (SPAN) questionnaire is a brief self-administered measure of dietary

intake that is frequently used for evaluating school-based nutrition education programs.^{5–7} Three versions of the questionnaire exist: one for high school (11th grade level), middle school (8th grade level), and elementary school (4th grade level). The questionnaires cover the same content, but are matched to age groups via reading level and cognitive demand. For example, the elementary school version contains fewer items and includes pictures of foods to facilitate recall and identification of items by children.

The factor structure of the SPAN questionnaire has not been tested, however. Creating latent variables—which are unobserved variables that are inferred from observed variables through calculation—in structural equation modeling (SEM) offers numerous advantages over traditional statistical methods.^{8–10} For example, (a) SEM is a more clear and theoretically sound method for testing mean differences than ANOVA or MANOVA, in that it does not require the assumption of compound symmetry (an improbable assumption), (b) latent variables statistically separate true score variance from error variance, (c) SEM allows researchers to specify and test specific a priori hypotheses and relationships beyond mean differences (e.g., variance, covariance), and (d) SEM offers a clearer and more comprehensive analysis of relationships and changes.⁹ In practical terms, latent variables in SEM provide more power for statistical tests, give researchers more flexibility in analysis, and create clearer interpretations of results.

However, before a latent variable can be used in analysis, steps should be taken to ensure the variable is measured correctly. Primarily, the measurement of the latent variable should remain stable (referred to as measurement invariance), meaning that the relationships among the observed variables that form the latent variable (i.e., the loadings and error of each observed variable) should remain relatively stable across contexts and over time.^{9,11} Simply measuring the same variables at different time points does not always mean the observed variable relationships will remain stable.⁹ If these relationships change between groups or over time, it could mean the same latent variable is not being measured across contexts, and thus scientific inferences become inaccurate. In other words, any differences in means could be interpreted as a result of comparing two different variables.¹¹ The stability of a latent variable can be tested by systematically holding factor loadings and error terms invariant over time and over groups in SEM, and testing the fit of the model and the change in fit of the model after each subsequent constraint. If the model continues to fit the data well after constraints are added, then it can be concluded that the relationships among the observed variables are stable (i.e., there is measurement invariance). For example, if a model that constrains parameters to be equal across two groups fits the data equally well as a model that allows those same parameters to vary across groups, then those parameters are said to be invariant across those groups.

The purpose of the present research is to test for the existence (and stability) of a *Healthy Foods* latent variable among four food consumption subscales from the SPAN questionnaire (Fruits, Vegetables, Milk, and 100% Fruit Juice). First, we will test to see if calculating a factor score is a better representation of the data than simply summing the subscales. We will then test the stability of the Healthy Foods latent variable by constraining factor loadings, variable means, and error terms to be equal across three time points, and then again across gender and study groups (i.e., intervention vs. control groups). We hypothesize that

the four observed variables specified will represent a stable latent variable that can be used by researchers in future analysis.

METHODS

The present work is a secondary analysis of data from a previously published report on a school-based nutrition intervention, in 3rd grade classrooms from the Shaping Up My Choices program developed by the Dairy Council of California and tested during the 2010–2011 school year.¹² The study had a sample size of 1,147 students (675 complete cases) and featured a randomized controlled design with pre- (0 weeks), post- (10 weeks), and follow-up (~22 weeks) assessments of nutrition knowledge, outcome expectancies, self-efficacy, and dietary intake. The study was approved by the ethics committee of the Institutional Review Board at Independent Review Consulting, Inc. Written informed assent was obtained from all minors and a passive parental consent procedure was used (i.e., if the parent did not decline consent, the minor was approached for consent). More detail of the program can be found at www.HealthyEating.org/SMC or in the previously published report.¹²

The SPAN questionnaire was used to measure dietary intake. Only the Fruits, Vegetables, 100% Fruit Juice, and Milk subscales are reported here. All four subscales were single items. The items read: “Yesterday, how many times did you eat fruit? **Do not count 100% fruit juice.**”; “Yesterday, how many times did you eat vegetables? Include all cooked and uncooked vegetables and potatoes. **Do not count French fries or chips.**”; “Yesterday, how many times did you drink fruit juice? Fruit juice is a 100% juice drink like orange juice, apple juice, or grape juice. **Do not count punch, Kool-Aid®, sports drinks, and other fruit flavored drinks.**”; and “Yesterday, how many times did you drink any kind of milk? **Include chocolate or other flavored milk and drinks made with milk.**” The answer options were ‘none’, ‘1 time’, ‘2 times’, or ‘3 or more times’. All three versions of the SPAN questionnaire have been tested and found to have adequate reliability and validity.^{5–7}

The majority of data analyses were done in R (R version 2.15.2, R Core Team, 2012) using the Lavaan package (Lavaan version 0.5–10, Rosseel Y, 2012). The effect of classroom clustering was tested using Stata (StataSE Release 12, StataCorp LP., College Station, TX, 2011): it exhibited a negligible effect (<5% of the total variance) and is not discussed further. The goal of the analysis was to test for a stable factor structure (i.e., measurement invariance) for a Healthy Foods latent variable by analyzing adequacy of model fit after progressively constraining the factor loadings, means, and errors of the observed variables over time and across subgroups of participants (specifically, gender and study group).¹¹ We can conclude a stable latent variable exists that can then be used in future analysis if the model continues to fit the data well after: (a) adding constraints over time, and (b) adding constraints across groups. Model fit was determined using a combination of the minimum function chi-square (χ^2), degrees of freedom (*df*), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). Conventional standards for good fit are values above 0.90 for the CFI and TLI and values below 0.08 for the RMSEA. Missing data was handled using Full Information Maximum Likelihood estimates.

RESULTS

The measurement model tested is shown in Figure 1a with values for Model 1d. Following guidelines suggested for SEM diagrams,¹³ observed variables are drawn as squares and unobserved (latent) variables are drawn as circles. All model parameters are shown as two-headed or one-headed arrows. Two-headed arrows with both heads pointing to the same variable represent variances (for latent variables) or error terms (for observed variables). A fixed variable set at 1 and drawn as a triangle is included to represent mean scores. Arrows deriving from this fixed variable represent group means.

First, a Rasch model (Model 1a) forcing all factor loadings to 1.00 was compared to a weak invariance model (Model 1b) that allows factor loadings to differ across subscales while being invariant over time.^{14,15} The Rasch model is equivalent to calculating summed composite scores, while the weak invariance model calculates latent variables with stable loadings over time. Fit indices are presented in Table 1. The weak invariance model yielded a significantly better fit to the data than the Rasch model (change-in- $\chi^2 = 124.62$ on 3 *df*, *p* < .001), indicating that calculating a latent variable is a better fit to the data than simple summation.

The next series of models tested for latent variable invariance (i.e., stability of the latent variable) over time using the complete sample. That is, the goodness of fit of a weak invariance model (constrained loadings; Model 1b), strong invariance model (constrained loadings and means; Model 1c) and strict invariance model (constrained loadings, means, and errors; Model 2d) were evaluated.¹⁵ The logic is that if the model continues to fit the data well after adding these constraints, then the latent variable is stable over time. Indeed, all three models yielded good fit to the data based on the fit indices shown in Table 1. The most restricted model (a “strict invariance” model) yielded a very good fit to the data, with χ^2 (*df* = 59) = 59.75, CFI = 1.00, TLI = 1.00, RMSEA < 0.01. In this model, Fruits had the highest factor loading (1.36), followed by Vegetables (1.00), 100% Fruit Juice (0.95), and Milk (0.56), and the sample had a mean Healthy Foods score of 1.05 at time 1, 0.97 at time 2, and 0.97 at time 3.

Finally, to test the stability of the latent variable across groups, grouping variables for study group (Model 2a and Model 2b) and gender (Model 2c and Model 2d) were added to the strict invariance model (Table 2). For each grouping variable, we: (a) allowed constraints to vary across groups, (b) held constraints invariant across groups, and (c) compared the fit of models from step (a) and step (b). If the latent variable is stable across groups, the more constrained model (step b) should yield a good fit to the data and show a similar level of fit as the less constrained model (step a). The logic is that if the model fits the data well when constraints are held across the groups, then the latent variable is stable.

Models 2a and 2b test the stability of the latent variable across study group. Based on fit indices presented in Table 2, both models yield a good fit to the data. Furthermore, there was only a negligible worsening of fit for Model 2b after constraining parameters across study group (change in $\chi^2 = 17.68$ on *df* = 10), indicating the latent variable is stable across groups.

Similarly, Models 2c and 2d test the stability of the latent variable across gender. Based on fit indices presented in Table 2, both models yield a good fit to the data. There was a slight worsening of fit for Model 2d after constraining parameters across gender (change in $\chi^2 = 27.71$ on 10 df), indicating the model fits better when parameters are free to vary across gender. However, this is a relatively small difference in model fit, and Model 2d still showed very good fit overall. Therefore, we can conclude that the latent variable was stable across gender.

DISCUSSION

The improvement of the weak invariance model (1b) over the Rasch model (1a) justifies the utility of calculating factor scores. Furthermore, the resulting sequences of fit of the “weak”, “strong”, and “strict invariance” models indicated that the Healthy Foods latent variable remained stable over time. Lastly, there was a relatively small worsening of fit when relaxing constraints across gender, a negligible worsening of fit when relaxing constraints across study group, and all strict invariance models tested yielded a very good fit to the data. Thus, it can be concluded that the Healthy Foods latent variable is stable over time and across various groups, and therefore can be used in future analysis.

There are several limitations to the generalizability of this study. First and foremost, it was conducted on 3rd grade students, all of whom were in the state of California. Thus, these findings should be replicated in students from other elementary grade levels (as this is the elementary version of the questionnaire), and students from other regions of the country. Additionally, the versions of the SPAN questionnaire designed for older participants (8th and 11th grade) would need to be tested to determine if a similar factor exists for those age groups.

IMPLICATIONS FOR RESEARCH AND PRACTICE

Treating these four dietary subscales from the SPAN questionnaire as a single latent variable offers several advantages for future research. One advantage is that it enables the study of within-person changes in Healthy Foods consumption using the SPAN questionnaire. Prior studies have advocated the SPAN questionnaire for only testing between-group differences due to the 1 day nature of the recall questions not necessarily being indicative of typical consumption.⁶ However, using four items in the form of a single latent variable may provide enough information from each child for exploring within-group changes.

Another advantage is that these SEM models can easily be altered to include a longitudinal change score that takes into account the overall pattern of healthy eating among these four subscales, as pictured in Figure 1b. In this latent change score model, a Change in Healthy Foods score (DHF) is created by setting the regression path between time 1 and time 2 equal to 1, implying that some portion of the time 2 score is exactly equal to time 1, and the residual variable (DHF) is directly interpretable as a change score.⁹ Once a change score is created, multiple group invariance modeling can be used to test for differences in means and variances across treatment groups. Furthermore, change scores can be predicted via

regressing the change score on other variables of interest (e.g., self-efficacy, social support, gender).

A clear example of the benefits of a latent change score model can be seen in analysis of the current data. In the published report,¹² no significant differences were found between study groups on these four food subscales at post intervention ($p < 0.05$). However, when the data is reanalyzed using the Healthy Foods latent change score (Figure 1b), a significant difference is found (difference = .08, change in $\chi^2 = 3.88$ on 1 df , $p = 0.04$). The control group significantly declined by $-.122$ unstandardized units of Healthy Foods per day from time 1 to time 2 ($p < 0.001$), whereas the intervention group declined by $-.04$, which was insignificant ($p = 0.15$). Although this daily difference is relatively small, it may accumulate to a meaningful difference in dietary intake across longer periods of time. However, whether this difference would lead to clinical changes in health is unknown.

In conclusion, this research provides support for a Healthy Foods latent variable consisting of four subscales from the SPAN questionnaire: Fruits, 100% Fruit Juice, Vegetables, and Milk. A series of strict invariance measurement models showed that the Healthy Foods latent variable remained stable across three time points, across gender, and across study groups. Thus, evidence supports calculating a Healthy Foods latent variable in future analysis of studies using the elementary SPAN questionnaire. It also enables testing longitudinal change scores that have more power, are more informative, and are more clearly interpretable than traditional methods.

Acknowledgments

This work was supported by the Dairy Council of California and the American Cancer Society (118283-MRSGT-10-012-01-CPPB).

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Figure 1.

Path model of the measurement model with numerical results from Model 1c (Figure 1a), and path model of Healthy Food latent variable with change scores (Figure 1b).

Note. HF = Healthy Food latent variable; Mi = Milk intake; Ju = 100% Fruit Juice intake; Fr = Fruit intake; Veg = Vegetable intake; DHF = Change in Healthy Food latent variable.

Numerical Results for Healthy Food Latent Variable Measurement Model Fitted to Whole Sample Across Three Time Points (n = 956).

Table 1

Parameters	Model 1a: Rasch model		Model 1b: Weak invariance		Model 1c: Strong invariance		Model 1d: Strict invariance	
	<i>M</i>	<i>S</i>	<i>M</i>	<i>S</i>	<i>M</i>	<i>S</i>	<i>M</i>	<i>S</i>
Factor loadings (invariant over time)								
Vegetables	1.00	=	1.00	=	1.00	=	1.00	=
Fruits	1.00	=	1.37	0.09	1.37	0.09	1.36	0.09
Fruit Juice	1.00	=	0.95	0.06	0.95	0.06	0.95	0.06
Milk	1.00	=	0.56	0.05	0.56	0.05	0.56	0.05
Goodness of fit indices								
χ^2/df	172.10 / 48		47.48 / 45		50.32 / 51		59.75 / 59	
CFI/TLI	0.94 / 0.92		1.00 / 1.00		1.00 / 1.00		1.00 / 1.00	
RMSEA	0.05		0.01		< 0.001		0.004	

M = maximum likelihood estimate; *S* = standard errors.

Numerical Results for Healthy Food Latent Variable Measurement Model Fitted Across Study Group and Gender.

Table 2

	Split by study group (n = 953)						Split by gender (n = 948)					
	Model 2a			Model 2b			Model 2c			Model 2d		
	Intervention	Control	Groups invariant	Males	Females	Groups invariant	Males	Females	Groups invariant	Males	Females	Groups invariant
Parameters	M	S	M	S	M	S	M	S	M	S	M	S
Factor loadings (invariant over time)												
Vegetables	1.00	—	1.00	—	1.00	—	1.00	—	1.00	—	1.00	—
Fruits	1.34	0.12	1.35	0.12	1.35	0.08	1.59	0.14	1.18	0.11	1.37	0.09
Fruit Juice	1.03	0.09	0.89	0.08	0.95	0.06	1.00	0.09	0.94	0.09	0.96	0.06
Milk	0.52	0.07	0.57	0.07	0.56	0.05	0.65	0.08	0.49	0.07	0.57	0.05
Goodness of fit indices												
χ^2/df	126.72 / 118			143.04 / 128			122.01 / 118			149.72 / 128		
CFI/TLI	1.00 / 1.00			0.99 / 0.99			1.00 / 1.00			0.99 / 0.99		
RMSEA	0.01			0.02			0.01			0.02		

M = maximum likelihood estimate; *S* = standard errors.