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Internal validity of the Food Access Survey Tool in assessing household food insecurity in rural Zambia

Muzi Na [1] · Alden L. Gross [2] · Lee S. F. Wu [1] · Bess L. Caswell [1] · Sameera A. Talegawkar [3] · Amanda C. Palmer [1]

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Abstract We assessed the internal validity of the Food Access Survey Tool (FAST) using data from households ($n = 907$) enrolled in an efficacy trial of biofortified maize in rural Zambia. This scale assesses food insecurity over a 6-month recall period. A Rasch partial credit model was used to evaluate item performance. Unidimensionality was assessed by principal component analysis, monotonicity was assessed by non-parametric methods, and differential item functioning (DIF) by several characteristics was assessed by cumulative ordinal logistic regression models. One item (frequency of consuming three square meals) did not fit the partial credit model. The remaining eight items fit in a primary single statistical dimension and item category severity increased monotonically with increasing severity of food insecurity. We identified statistically significant DIF in three subgroup comparisons, but effect sizes of total DIF were considered practically insignificant (<2 %). After excluding the item on "square meals," the FAST serves as an internally valid tool to measure household food insecurity in rural Zambia.

Keywords Food insecurity · Internal validation · Item response theory · Rasch model · Zambia

✉ Amanda C. Palmer
apalme17@jhu.edu

1 Center for Human Nutrition, Department of International Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA

2 Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA

3 Department of Exercise and Nutrition Sciences, Milken Institute School of Public Health, The George Washington University, Washington, DC, USA

Introduction

Despite declines in the prevalence of undernutrition over the past 20 years, food insecurity remains a major public health problem in Sub-Saharan Africa (FAO et al. 2014). Practical and accurate methods are greatly needed to assess food insecurity in this part of the world. Beyond providing estimates of national or regional prevalence, food insecurity measures at the individual- and household-levels are crucial to differentiate the food-insecure from the food-secure, to monitor severity and progress at regional and community levels, and to target programs (Webb et al. 2006). However, simple methods to assess the dynamics and severity of food insecurity are challenging due to the multi-dimensional and latent nature of the food insecurity concept, which lacks direct measurable indicators (FAO. 2002; Webb et al. 2006).

The development of measures for household food insecurity is increasingly focused on capturing a set of experiences and/or behaviors that are associated with food access stresses. Such experiences may cover an array of sub-domains, including psychological concerns, adaptations to cope with inadequate food quality and/or food quantity, socially acceptable strategies to cope with short and long term food insecurity, and physical consequences of hunger (Coates et al. 2006a). Food insecurity is commonly accepted to be a "managed process" (Radimer et al. 1992). As such, the related experiences and coping behaviors would theoretically evolve with progressive difficulty in food access, i.e., anxiety regarding food possession would occur before actual strategies that compromise food quality and then food quantity. The nature, frequency and intensity of those experiences are believed to reflect the severity of food stresses (Ruel et al. 2010) and the purpose of behavior-based scales is to order households along a food insecurity continuum by capturing those behavior attributes (Jones et al. 2013).

Over the past two decades, researchers have developed many context-specific behavior-based scales, surveys or indices to capture food accessibility at the household level. The U.S. Department of Agriculture's Household Food Security Survey Module (Nord and Bickel 2002), for example, assesses the key food insecurity domains of uncertainty and worry, inadequate quality, insufficient quantity, and hunger / physical consequences. A separate Coping Strategies Index, developed by the World Food Programme and CARE (Maxwell and Caldwell 2008), enables researchers to construct a score based on a list of weighted context-specific coping strategies applied under food deprivation. Ethnographic research has also guided development of questionnaires, such as the Food Access Survey Tool (FAST) (Coates et al. 2003), which includes domains similar to the above, as well as questions related to socially acceptable coping strategies. Adaptation and validation of the assessment tools are critically important and highly recommended before a tool developed in one context can be applied in another (Perez-Escamilla et al. 2004; Studdert et al. 2001; Menon et al. 2002). Cross-cultural comparisons must be interpreted with caution, as score performance depends both on the food insecurity situation and how items on behavior-based scales are interpreted by respondents in each context. Coping behaviors may vary widely and may not always reflect the same degree of severity in different populations (Maxwell et al. 2008; Deitchler et al. 2010). Differences between the food insecurity score distribution were obvious in a multi-country study, even when assessing universal experiences of food insecurity using the same scale (Psaki et al. 2012).

Our goal was to assess the internal validity of the FAST for use in rural Zambia using the Rasch model—a parametric approach that models item-wise response patterns. Rasch modeling is commonly used to assess "severity" in food security assessment (Coates et al. 2006b; Gulliford et al. 2004; Melgar-Quinonez et al. 2007; Derrickson et al. 2000; Connell et al. 2004; de Toledo Vianna et al. 2012; Deitchler et al. 2010). Modeling under item response theory enables us to estimate the item-wise severity parameters by allowing different items to reflect different levels of household food insecurity. This approach is theoretically appropriate to the "managed process." Empirical data can then be used to make comparisons between estimated item severity and theoretical expectations. Rasch models require several key assumptions. If assumptions are met and the model fits the data well, a simple summed score of affirmed responses would contain sufficient information to rank latent household food insecurity (Masters. 1982), a desirable property for operational use of the food insecurity scales. Therefore in this study, we also checked the key model assumptions. We considered the scale to be internally valid if items measured only one food insecurity trait and performed according to theory in terms of the order and direction of item severity estimates.

Methods

Subjects and data collection

Eligible preschool-aged children from 907 households were enrolled in a cluster-randomized, placebo-controlled intervention trial in rural Mkushi District, Central Province, Zambia. The trial aimed to test the preventive efficacy of provitamin A carotenoid biofortified maize in comparison with conventional white maize and non-intervened control on child vitamin A status (Palmer et al. 2016). Informed consent was obtained for all participating children in this study from a parent or guardian by trained field interviewers prior to the baseline assessment (September 2012). Interviewers then administered a questionnaire to the parent or guardian, including the FAST module and questions on socio-economic status, capturing information on the household heads' literacy, occupation, family religion, tribe affiliation, predominant language spoken in households and asset ownership.

The FAST is a 9-item Likert scale that has been developed and validated in Bangladesh to assess household food insecurity (Coates et al. 2003). It was adapted for our Zambia study setting by changing questions regarding staple crop consumption from rice to maize. As part of the baseline household-level interview, we asked respondents to recall the frequency of concerns over food acquisition, reductions in food quality and quantity, and strategies used to cope with household food insecurity over the prior 6-month period. Responses were coded as: 0 = never (0 times in the past 6 months);1 = rarely (1–3 times / 6 months); 2 = sometimes (4–6 times / 6 months); 3 = often (a few times each week) or 4 = mostly (most days per week). The question regarding how often the respondent consumed three "square meals" a day was reverse-coded because it was the only question about sufficiency instead of deprivation. Households with missing data in FAST items were excluded from the internal validity analysis.

The study protocol was approved by the Ethical Review Committee at the Tropical Diseases Research Centre in Ndola, Zambia and the Institutional Review Board of the Johns Hopkins Bloomberg School of Public Health in Baltimore, Maryland.

Statistical analysis

The partial credit model, an extension of the Rasch model for polytomous responses, is commonly used for Likert scale analysis (Pallant and Tennant 2007). The probability of a person choosing an item response is modeled as a stepped logistic model between adjacent categories of both the individual's food insecurity latent and item step severity parameters.

Rasch models have four key assumptions: 1) only one food insecurity latent trait accounts for the inter-item associations in the data (unidimensionality); 2) the probability of endorsing a response will increase or remain constant, but never decrease, as the food insecurity latent trait increases (monotonicity); 3) the responses to each item on the scale do not differ by respondent characteristics considered exogenous to food insecurity, e.g., education, religion, language (measurement invariance); and 4) the relationship between responses to any two items are independent, conditioning on the underlying food insecurity latent trait (local independence).

To examine how well our data fit the Rasch partial credit model, we first calculated the standardized residual between the expected and actual responses for each item. We then derived the mean estimate of item fit by squaring, summing and averaging the individual standardized residual of all items on the scale. We used the weighted statistic for item fit, known as Infit, which gives more weight to the household's food insecurity severity around the parameter estimates, similar to previous food security scale analyses (Melgar-Quinonez et al. 2007; Hackett et al. 2008; de Toledo Vianna et al. 2012). Infit statistics for each response category were estimated based on residuals calculated from two adjacent categories. For polytomous data, Infit statistics are more stable over increasing sample sizes than t-statistics, so we report the mean estimate of Infit statistics rather than t-statistics (Smith et al. 2008). The Infit is expected to be 1.0 if the observed data fit the model perfectly. A range of 0.7 to 1.3 is considered acceptable while a narrower range 0.8 to 1.2 is recommended (Connell et al. 2004). Both ranges were used to compare Infit statistics of the nine items.

We then estimated the item categorical severity by calculating Thurstonian thresholds from the item step severity parameter of the model. The Thurstonian threshold, which represents category difficulty for polytomous items, is interpreted as the food insecurity latent score on logit scale at which the probability of choosing a category or higher reaches 0.50 (Wu and Adams 2007). Within each item, a higher response category is expected to have greater item category severity than the lower response categories. We compared results with theoretical expectations.

Finally, we conducted model assumption assessments. Unidimensionality was tested by calculating Cronbach's α and Loevinger's scalability coefficient (H), as well as by principal component analysis (PCA). Cronbach's α is a measure of internal consistency or item inter-correlations. The α value ranges from 0 to 1 with 0 indicating perfect independence and 1 indicating perfect correlation among all items. A value of 0.7 or greater is considered satisfactory to indicate unidimensionality (Bland and Altman 1997). The H coefficient is an indicator of scale homogeneity. H was calculated as the ratio between the sum of item pair-wise covariance and sum of the maximum item pair-wise covariance (Stochl et al. 2012). Scales with $H > 0.4$ or >0.5 are considered as medium-level or strongly unidimensional (Ligtvoet et al. 2010). PCA on polychoric correlation matrix was used to detect the number of components among scale items (Wold et al. 1987). Unidimensionality is supported if: 1) only the first component has an observed eigenvalue greater than 1; 2) variance explained by the first component is greater than 2/3 of total variance; and 3) only the first component has the observed eigenvalue greater than the simulated eigenvalue, which is calculated from the parallel analysis on item correlation matrix that is due to chance alone (Hattie. 1985; Kaiser et al. 2002; Timmerman and Lorenzo-Seva 2011).

To examine monotonicity, we used the non-parametric method by the R/Mokken package 2.7.5, which compares the probability of endorsing an item category or above given the summed score of the remaining items (Stochl et al. 2012). If monotonicity holds true, the probability of affirming the examined item category should be greater among households with higher summed scores of the remaining items than households with lower summed scores. A violation was flagged if the expected order was reversed and local decrease of item response probability was seen. A minimum value for detecting any reverse order was set at the default value (Stochl et al. 2012). We set the minimum number of households within each adjacent summed score group at 84, which was one tenth of the total sample size, to avoid potential sampling errors (Stochl et al. 2012).

We assessed measurement invariance of the FAST by testing differential item function (DIF) across three subgroups, defined by the households head's literacy status (literate vs. illiterate), respondent's household position (household head vs. other), and primary language spoken (Bemba vs. other). We used cumulative ordinal logistic regression to examine DIF, as it simultaneously detects both uniform DIF, which occurs consistently regardless of the latent food insecurity severity level, and non-uniform DIF, which may vary by the latent severity (Kristjansson et al. 2005). We first checked the proportional odds assumption and then loosened to generalized ordered logistic regression methods for four items because assumption violations were detected in those items. In model 1, the log odds of response in one category or below was modeled as a linear function of the total food insecurity score alone. In model 2, the total score, group membership, and an interaction term between the total score and group membership were used to model log odds of responses. Log likelihood ratio tests were conducted to test the statistical significance of the total DIFs between the two nested models. The practical significance of total DIF was assessed by the effect size, which is the difference of R-squared between model 2 and 1. We used a cutoff of 13 % as indicative of practical significance (Zumbo. 1999).

As in previous validation studies, we relied on the model fit results to test the assumption regarding local independence of polytomous items (Coates et al. 2006b; de Toledo Vianna et al. 2012; Hackett et al. 2008).

We used R 3.1.1 (The R Foundation for Statistical Computing) to conduct all of the analyses and the TAM (Test Analysis Modules) package 1.0-3 to build the partial credit models, calculate model fit statistics, and to estimate item severity parameters.

Results

We enrolled $n = 907$ households in the biofortified maize trial, of which household-level baseline interviews were conducted in 896 households (Table 1). 30.0 % of respondents were household heads. 84.6 % of household heads were literate. About one third of the household heads were primarily involved in salaried employment (31.4 %), while 16.0 %, 28.1 %, and 24.5 % worked in farming, self-employed jobs or small businesses and other fields, respectively. The majority of households reported a Christian denomination as their family religion (86.2 %). Households were primarily from the Lala and Bemba tribes (40.6 % and 24.4 %, respectively) and primarily spoke these languages within their households (31.6 and 59.9 %). The present analysis includes $n = 846$ households for whom complete data were available for all FAST items. Households with missing or "don't know" responses to one or more FAST items did not differ markedly in terms of any socio-economic variables (data not shown).

Responses to FAST items (Table 2) generally followed a decreasing trend from "never" to "mostly," with the proportion of "never" responses ranging from 16.8 to 75.5 %. Only the "square meals" item differed: it was more uniformly distributed across the five response categories from "never" to "mostly," with proportions of 16.8 %, 24.4 %, 17.4 % 15.6 % and 25.9 %, respectively. The majority of Infit values were within the range from 0.8 to 1.2 (Fig. 1), suggesting adequate item fit. Again the "square meals" item was an exception. The last three categorical Infit values for this item exceeded the acceptable upper cutoff (Sometimes = 1.35; Often = 1.51; Mostly = 1.39). Given its poor fit to the partial credit model, the "square meals" item was excluded from subsequent analyses. 108 (12.8 %) households reported "never" to all 8 items.

Item categorical severity estimates from the model were well-dispersed along the continuum of latent severity, which was on a standard normal distribution N(0,1) (Fig. 2, panel a), except on the far left of the distribution, which included food secure households or those with very mild food insecurity. All items displayed increasing categorical severity (Thurstonion threshold) from "rare" to "mostly" responses (panel b). We also observed a range of coverage of item severity along the food insecurity spectrum. For example the logit severity parameter ranged from −0.52 for "worry about food" to 1.08 for "eat other grains" of the "rare" category and from 1.13 for "purchase maize" and 3.43 for "run out of food" of the "mostly" category, respectively.

All tests of model assumptions excluded the "square meals" item. In terms of unidimensionality, Cronbach's

Table 1 Characteristics of the study population ($n = 907$)

Characteristics	Number[a]	Percent
Respondent	896	
Household head		30.0
Spouse of household head		62.3
Others		7.7
Household head characteristics		
Literacy	876	84.6
Occupation	887	
Farming		16.0
Salaried employment		31.4
Self-employment/ small business		28.1
Other		24.5
Household characteristics		
Religion	896	
Christian denomination[b]		86.2
Other		12.8
None		1.0
Tribe affiliation	896	
Lala		40.6
Bemba		24.4
Other		34.9
Primary language	895	
Lala		31.6
Bemba		59.9
Other		8.5
Electricity at home	896	5.0
Asset ownership		
Radio	895	65.6
TV	895	35.8
Bicycle	896	53.9
Mobile phone	896	71.4

[a] Baseline data were missing for 11 out of 907 enrolled households

[b] Catholic, Seventh Day Adventist, Anglican, Jehovah's Witness/ Watchtower, Baptist, United Church of Zambia and Pentecostal were categorized as Christian denomination

Table 2 Responses to the Food Access Survey Tool ($n = 846$)

Original question		Item description	Responses (%)				
			Never	Rarely	Some-times	Often	Mostly
In the past 6 months, how often did…							
Item 1[a]	you eat three 'square meals' (full stomach meals) a day	Square meals	16.8	24.4	17.4	15.6	25.9
Item 2	you or any of your family have to eat sorghum (or another grain) although you wanted to eat maize (not including when you were sick)?	Eat other grains	75.5	15.0	6.3	2.7	0.5
Item 3	you yourself skip entire meals due to scarcity of food?	Skip entire meals	46.3	31.8	15.3	4.5	2.1
Item 4	you personally eat less food in a meal due to scarcity of food?	Eat less	37.6	35.7	17.6	6.7	2.4
Item 5	food stored in your home run out and there was no money to buy more that day?	Run out of food	45.7	33.2	13.7	6.5	0.8
Item 6	you worry about where food would come from?	Worry about food	34.6	34.4	17.7	7.1	6.2
Item 7	your family purchase maize?	Purchase maize	35.8	19.5	13.5	13.8	17.4
Item 8	your family take food (maize, beans, etc.) on credit (or loan) from a local shop?	Take food on credit	72.5	17.6	7.1	2.0	0.8
Item 9	your family have to borrow food from relatives or neighbors to make a meal?	Borrow food	64.1	26.6	6.6	2.3	0.5

[a] Item 1 is reverse-coded in the analysis; the item description for the reversed item 1 is "no square meals"

α and the scalability coefficient H for the remaining eight items was 0.77 and 0.36, respectively. Observed eigenvalues from the PCA for the eight components were 3.94, 0.99, 0.90, 0.74, 0.45, 0.40, 0.30 and 0.29, with the first component explaining 49 % of the total variance. The eigenvalue of the first component only was greater than the simulated eigenvalues from parallel analyses, which valued the eight components as 1.14, 1.09, 1.05, 1.02, 0.98, 0.95, 0.91, and 0.86, respectively.

For monotonicity (Table 3), the number of active comparisons in the first column was determined by the number of summed score groups. Although local decreases in item response probability was found in items regarding "eat other grains", "purchase maize", "take food on credit" and "borrow food," there were few violations of monotonicity (≤2) and none were statistically significant.

Likelihood ratio tests indicated statistically significant DIF for all eight items comparing households with heads who were literate versus those who were illiterate (Table 4). When comparing respondents who were household heads versus other people, significant DIF was only found in "eat other grains" and "purchase maize". By primarily language (Bemba versus other), "run out of food" and "borrow food" displayed significant DIF. Effect sizes for all items in group comparisons ranged from 0 to 1.3 %, far below the recommended cutoff of 13 % for diagnosis of practically significant DIF.

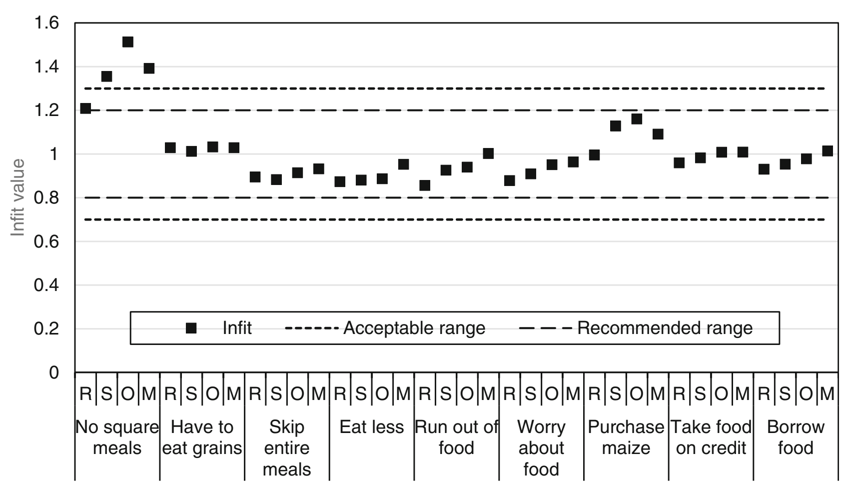

Fig. 1 Infit statistics of the adapted FAST by item and by category ($n = 846$). *R* rare, *S* sometimes, *O* often, *M* mostly

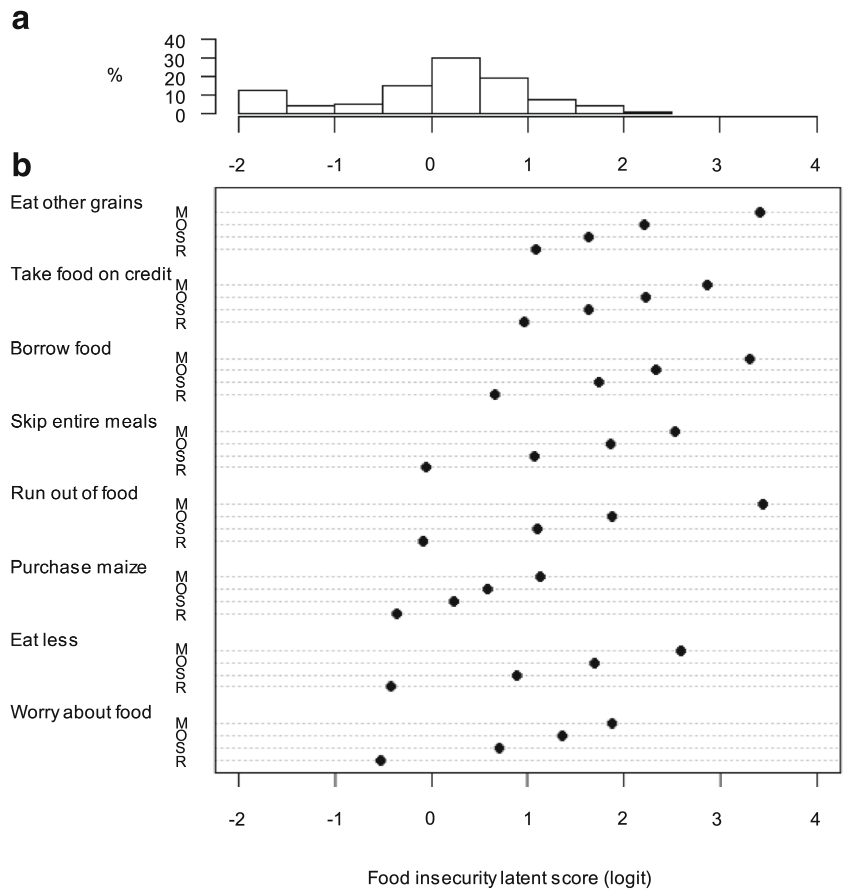

Fig. 2 The distribution of **a** estimated household food insecurity latent score and **b** item category severity on logit scale ($n = 846$). *R* rare, *S* sometimes, *O* often, *M* mostly

Discussion

We have demonstrated general internal validity of the adapted FAST for assessing household food insecurity in rural Zambia. Item fit assessment from the partial credit model suggested the removal of the item regarding the frequency of square meals. The remaining eight items primarily fit in one statistical dimension and their ordered responses displayed satisfactory monotonicity along the latent food insecurity trait. DIF was detected on some FAST items as found in previous validation work in Bangladesh (Coates et al. 2006b; Na et al. 2015); however, none was of practical concern because of the small additional variances that can be explained by the total DIF. Given findings on model fit and assumptions, a summed score of the polytomous eight-item FAST should be an internally valid index to measure cross-sectional food insecurity in rural Zambia. Sensitivity analysis indicated that our results were not sensitive to small counts in category responses of some items (data not shown).

Like other behavior-based food insecurity scales, the FAST is a simple assessment tool that covers multiple key domains of food insecurity (Coates et al. 2006a). However, unlike tools

Table 3 Violation of the monotonicity assessment by Mokken method

Item	No. of active comparisons	Violation of monotonicity		
		No.	%	No. of significant results
Eat other grains	46	1	2	0
Skip entire meals	53	0	0	0
Eat less	61	0	0	0
Run out of food	47	0	0	0
Worry about food	55	0	0	0
Purchase maize	84	2	2	0
Take food on credit	42	1	2	0
Borrow food	59	1	2	0

Table 4 Likelihood ratio test between two nested cumulative ordinal logistic regression models for DIF examination[a]

Item	Literacy (literate vs illiterate)					Household head (Yes vs No)				Language (Bemba vs other)			
	Model 1[b]	Model 2[c]	−2LL	*P*	Effect size[d]	Model 2[c]	−2LL	*P*	Effect size[d]	Model 2[c]	−2LL	*P*	Effect size[d]
Eat other grains	−591.9	−571.6	40.7	<0.001	1.2 %	−583.28	17.3	0.03	1.3 %	−587.9	8.0	0.44	0.6 %
Skip entire meals	−737.7	−716.1	43.4	<0.001	0.3 %	−737.40	0.7	0.71	0.0 %	−737.7	0.1	0.96	0.0 %
Eat less	−780.2	−758.5	43.3	<0.001	0.1 %	−778.32	3.7	0.16	0.2 %	−779.7	0.9	0.64	0.0 %
Run out of food	−754.8	−727.5	54.7	<0.001	1.0 %	−753.99	1.7	0.99	0.1 %	−747.2	15.2	0.05	0.7 %
Worry about food	−843.7	−814.3	58.7	<0.001	0.7 %	−840.49	6.4	0.60	0.3 %	−840.6	6.1	0.63	0.3 %
Purchase maize	−1088.3	−1059.9	56.7	<0.001	0.2 %	−1080.22	16.1	0.04	0.6 %	−1082.0	12.5	0.13	0.5 %
Take food on credit	−603.9	−581.5	44.8	<0.001	1.2 %	−602.85	2.1	0.36	0.1 %	−603.4	0.9	0.63	0.1 %
Borrow food	−632.1	−616.8	30.6	<0.001	0.3 %	−630.18	3.9	0.14	0.2 %	−629.8	4.6	0.10	0.3 %

[a] DIF, differential item function; -2LL, twice the difference in the log-likelihoods between model 2 and model 1

[b] Model 1: The log odds of response in one category or below is modeled as a linear function of total food insecurity score only

[c] Model 2: The log odds of response in one category or below is modeled as a linear function of total food insecurity score, group membership and interaction between total score and group membership

[d] Effect size is defined as the difference of R-squared between model 2 and model 1

developed for more universal cross-cultural assessments, such as the Household Food Insecurity Access Scale (HFIAS) (Coates et al. 2007), FAST also includes some context-specific questions related to resource augmentation strategies. These may or may not be commonly applied outside of Bangladesh, for which the tool was originally developed. Our data suggest that these coping behaviors were not uncommon in rural Zambia and that there was a reasonable range of variation in terms of the frequency that each coping behavior was adopted.

The misfit of the item 1 regarding the consumption of three "square meals" per day may due to several reasons. First, the validity of a food insecurity scale requires performance consistency, which is defined as the consistent understanding of the scale between respondents and developer's intention (Frongillo. 1999). "Square meals" or "full stomach meals" are common local terms in Bangladesh. However, these may lose their comprehensive sense via translation into the local Zambian language. Second, as an indicator of food quantity security, the item regarding "square meals" was termed on a daily recall basis ("three square meals a day"), yet the respondents were being asked to report on the average frequency over the past 6 months. Although this was not a challenge for respondents in Bangladesh (Coates et al. 2006b; Na et al. 2015), it may be possible that some respondents in Zambia misunderstood the time phases.

The distribution of the 8-item index was close to a normal distribution, as expected. However, more households than under the normal assumption reported negative responses to all items on the food insecurity scale. A similar clumping of the food insecurity index distribution has been previously reported from other resource-poor settings. In a multi-country study, Psaki et al. (2012) administered a similar 9-item food insecurity scale, HFIAS, in eight countries across South Asia ($n = 4$), Sub-Saharan Africa ($n = 2$), and Latin America ($n = 2$). Though an identical scale was applied across study sites, the proportion of households returning straight negative answers to the scale–therefore classified as "food secure" households–varied largely, from ~20 % in Pakistan to ~60 % in Nepal and Tanzania. When a large proportion of respondents stack on the "food secure" end, the scale may be unable to differentiate between food secure households and those with mild food insecurity. Respondents may also underreport experiences of food insecurity in sensitive socio-cultural contexts (Nanama and Frongillo 2012) and/or under well-adapted chronic food deprivation (i.e., they no longer perceive the problem) (Na et al. 2015). Researchers should bear in mind the subjective nature of perception-based scales and be aware of potential bias when using them.

The estimated severity of the eight items ranked in the theoretically expected sequence. Among all estimates, "worry about food" had the lowest severity, followed by "eat less," "purchase maize," "run out of food," and "skip entire meals". This supports the assertion that coping strategies were initiated and applied at different levels of household food insecurity. When food insecurity was mild, people were first affected by anxiety over food acquisition. As food scarcity progressed, households then adopted strategies to cope and even reduce the quantity of food consumed. Before food was completely depleted ("ran out of food"), household members were able to cut portions ("eat less") and to manage limited resources by purchasing the staple food more often, in smaller amounts each time ("purchase maize"). However, after food was depleted ("ran out of food"), severely food-insecure households have to reduce consumption to a greater extent ("skip entire meals"). Reaching out for help, borrowing food from relatives or neighbors or taking food on credit from shops, was applied at even more severe stages of food insecurity. Like the most food-insecure households in Bangladesh (Coates et al. 2006b; Na et al. 2015), switching from their usual staple food to less preferred alternatives was among the last things Zambian food-insecure households would do ("eat other grains").

A similar order of the severity weights was assigned to coping strategies in previous research on the Coping Strategies Index carried out in Zambia (Maxwell et al. 2008). The greatest discrepancy in item severity between these two studies was related to the consumption of less preferred foods. In FAST, eating non-preferred staples was the most severe item severity, yet in the Coping Strategies Index weighting scheme, eating less preferred foods (including staple and other foods) ranked as the least severe. Though questions in both tools were intended to capture the food quality domain, the FAST item was limited to staple foods only. It did not capture behaviors such as shifting to other less expensive and/or less nutritious foods that accompany the staple. Given that the demand for staple foods is less elastic (Bouis et al. 2011), it may be reasonable that changing staple preference represents higher insecurity severity in our sample.

Our study has some limitations. The DIF check was only performed by a few demographic sub-groups due to the limited number of variables collected during the trial's baseline assessment. Whether the FAST is valid for assessing the dynamic of food insecurity over seasons is outside the scope of this cross-sectional analysis, but should be considered in future longitudinal analyses with multiple FAST measures. This is particularly important given the seasonal variation in food insecurity that has been observed in rural Zambia (Cole and Tembo 2011) and elsewhere (Sahn. 1989). Future research should also explore the external validity of the summed score versus predictors and/or consequences of household food insecurity. Given that similar coping strategies are likely applied under food deprivation in other Sub-Saharan African countries, the FAST items could be useful for food insecurity assessments throughout the region. However, we recommend similar validity testing before the scale or any particular items are applied more broadly.

The FAST, excluding the item regarding the frequency in consuming three square meals per day, is an internally valid assessment tool to measure household food insecurity in rural Zambia. The summed score over the polytomous eight-item FAST is recommended for public health researchers as a simple, practical, and sufficient index to rank households along the food insecurity latent continuum.

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Compliance with ethical standards All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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Muzi Na Ph.D., M.H.S., is a postdoctoral fellow at the Johns Hopkins Bloomberg School of Public Health. Her research interests include food insecurity and socio-behavioral risk factors in relation to human nutrition and health. She is currently leading several projects looking at the relationship between socio-economic factors and food security, child feeding practices and women's care seeking behaviors in developing countries. She holds a Ph.D. in Nutrition and a M.H.S. in Biostatistics from Johns Hopkins University, a B.S. in Economics and a B. Medicine (M.D. equivalent) from Peking University, Beijing, China.

Bess L. Caswell M.S., is a doctoral candidate at the Johns Hopkins Bloomberg School of Public Health, Human Nutrition program. She completed her Master of Science degree in International Agricultural Development, specializing in International Nutrition, at the University of California, Davis. Her research interests are in dietary assessment methods, food security and dietary quality.

Alden L. Gross Ph.D., M.H.S., Assistant Professor of Epidemiology at the Johns Hopkins Bloomberg School of Public Health. He is a psychiatric epidemiologist with research interests include mental health and cognitive aging, integrative data analysis and data harmonization.

Sameera A. Talegawkar Ph.D., is an Associate Professor in the Department of Exercise and Nutrition Sciences at the Milken Institute School of Public Health, The George Washington University. She is a nutritional epidemiologist by training and has a Ph.D. in Nutrition from the Friedman School of Nutrition Science and Policy at Tufts University. Sameera has significant expertise in dietary assessment methodologies in diverse populations and her research focuses on the role of dietary and other lifestyle predictors of age-associated declines in the elderly, and on the determinants of health disparities in racial and ethnic minority populations.

Lee Shu-Fune Wu M.H.S., is a Senior Research Associate in the Center for Human Nutrition at the Johns Hopkins Bloomberg School of Public Health. She has more than 20 years of experience in research and data management. Her research is based primarily in Bangladesh, where she has been involved in a series of large-scale randomized controlled trials to test the preventive efficacy of food or micronutrient supplements on health and survival of mothers, infants, and young children. She is also involved in studies in Nepal, Malawi, Mozambique, and Zambia. She holds an M.H.S. in biostatistics from Johns Hopkins University.

Amanda C. Palmer Ph.D., M.H.S., is an Assistant Scientist in the Center for Human Nutrition at the Johns Hopkins Bloomberg School of Public Health. She has worked previously with UNICEF, Helen Keller International, and PeaceCorps. She is currently an investigator on a series of trials in Zambia to test the nutritional impact of regular biofortified maize consumption in infants, children, and lactating mothers. She holds a Ph.D. and M.H.S. in Human Nutrition from Johns Hopkins University, and a B.A. in Public Policy from the University of Chicago.