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Grains Are Similarly Categorized by 8- to 13-Year-Old Children

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Abstract

This study assessed how 8- to 13-year-old children categorized and labeled grain foods and how these categories and labels were influenced by child characteristics. The main hypotheses were that children categorized foods in consistent ways and these food categories differed from the professional food categories. A set of 71 cards with pictures and names of grain foods from eight professionally denned food groups was sorted by each child into piles of similar foods. There were 149 8- to 13-year-old children (133 English-speaking, 16 Spanish-speaking) in this exploratory study. One-way analysis of variance and Robinson matrices for identification of clusters of food items were calculated. Children created a mean (\pm standard deviation) of 8.3 ± 3.8 piles with 8.6 ± 9.1 cards per pile. No substantial differences in Robinson clustering were detected across subcategories for each of the demographic characteristics. For the majority of the piles, children provided "taxonomic-professional" (34.5%) labels, such as break for the professional category of pancakes, waffles, and flapjacks. These categories may be used to facilitate food search in a computerized 24-hour dietary recall for children in this age group.

Accurate measurement of children's food intake is necessary for research and practice (1). A 24-hour dietary recall is considered the preferred method of diet assessment (2) and is designed to record actual intake over a certain time period, obtaining specific foods, beverages, amounts, cooking procedures, seasonings, add-ons, locations, and times of food consumed (3). Conducting a detailed 24-hour dietary recall, however, can be cost-prohibitive for large studies and practice. A proto-type computerized 24-hour dietary recall (called the Food Intake Recording Software System or FIRSSt) for children was developed to minimize these costs, but only assessed fruit and vegetable intake (4). Research is needed to extend FIRSSt to cover all food groups.

The age at which children reach a level of cognitive development at which they can accurately report dietary intake is not clear (5). Some studies have obtained reasonable 24-hour dietary recalls from 8-year-old girls (6), whereas food frequencies have elicited data similar to that

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from adults only with children 13 years of age and older (7). Girls may be more reliable than boys (8), differences might be associated with ethnic groups (9), and underreporting has been associated with obesity (10). It is unknown how child characteristics affect the categorization or reporting of grain foods. Card sorts exploring how children categorized single food items (11), mixed dishes (12), and fruits and vegetables (13) found that child-generated categories accounted for 92% or more of the clustering variance, but the names of the categories only partially reflected a professional nutrition categorization or labeling of the foods.

Understanding how children categorize and label grain foods should identify how to group and name the food categories in a computerized 24-hour dietary recall to facilitate their accurate and rapid search. Grains are a diverse grouping of foods with different colors, textures (14), sweetness (15), and uses in meals (eg, bread for a sandwich, pancakes for breakfast). It is not clear to which characteristics children will attend in categorizing them. This study assessed how 8- to 13-year-olds categorized and labeled grain foods, and how these categories and labels were influenced by sex, age, body mass index (BMI), ethnicity, and socioeconomic status. The main hypothesis was that children categorize foods in consistent ways, and that these food categories will substantially differ from professional food categories.

METHODS

Sample Recruitment

This exploratory study had a sample of 149 children, aged 8 to 13 years, recruited via telephone from the Children's Nutrition Research Center's volunteer participant database, during the summer of 2006. Attempts were made to recruit a sample of 150 children with equal numbers of subjects in each ethnic (white, Hispanic, and African American) and age category. A special attempt was made to recruit a group of primarily Spanish-speaking children in anticipation of a Spanish language version of FIRSSt. Approximately 1,390 children were eligible from the city of Houston and vicinity. Recruitment stopped after 330 children were called; 54 were lost in the follow-up; of the 276 contacted, 210 verbally agreed to participate, but only 152 participants attended; 149 participants had complete data. The Baylor College of Medicine's Institutional Review Board approved this research.

Measures

Participant's demographic data (age, sex, ethnicity, parents' highest educational attainment, and family income) were obtained by parent report. BMI was calculated after measuring height and weight according to a standardized protocol using a stadiometer (PE-AIM-101, Perspective Enterprises, Portage, MI) and electronic scale (SECA Alpha 882, Baltimore, MD). The Centers for Disease Control and Prevention (CDC) BMI percentiles were obtained after calculating the BMI as kg/m² (16).

Card Sorting—Each child conducted five different unconstrained card sorts taking about 30 minutes each, one of which was analyzed for this manuscript. The sequence of card sort tasks was randomly assigned to minimize possible sequence and fatigue effects. Grain foods from eight professionally identified categories (17) were selected by a group of dietitians and behavioral researchers (Figure) to reflect those foods most frequently consumed by 8- to 13-year-old children from different ethnic groups. A colored photograph and name of each of the 71 selected food items were presented on $4\frac{1}{4} \times 5\frac{1}{2}$ -inch cards. The child was asked to sort the cards into piles of similar foods. At the completion of sorting the child was asked to name each pile and then explain why he/she had selected that particular name.

Data Processing and Analyses—Descriptive statistics (means, standard deviations, frequencies, percentages) were used with the anthropometric and demographic characteristics.

Children were separated into 8- to 10-year-old and 11- to 13-year-old categories, and into normal (BMI < 85th percentile) or overweight (BMI-for-age ≥85th percentile) categories based on CDC growth charts (CDC-BMI charts) (18). Differences in the mean number of card sort piles were tested across demographic and other variable categories using one-way analysis of variance and Tukey's pairwise comparisons.

The card sort naming process had two types of data coding: (a) adjustment of the first level names for consistency of names across children (second level codes); and (b) categorization of the second level codes into type of category (third level codes). To introduce consistency across the children, pile names such as "different kinds of rice," "rice group," and "rices" were uniformly labeled "rice" (second level name); "snack," "snack group," and "snack foods" were uniformly labeled "snacks." Two registered dietitians coded each child pile name, and disagreements were resolved by group consensus (among the authors). Previous studies categorized foods by cognitive organizing characteristics (19). Eleven third-level categories were used for categorization of the second-level food group names (see Table 1). These thirdlevel categories were sequenced reflecting cognitive development, ranging from simpler egooriented categories (evaluative-preferences: like/do not like), to categories requiring and imposing a cognitive framework reflecting knowledge of nutrition (taxonomic professional, nutrient composition). Definitions of these categories are in Table 1. Cross-tabulation assessed correspondence of the third-level categories with the original professional categories. (Table 1). The γ^2 statistic was used to test differences in distributions of the third-level categories by demographics.

Proximity matrices were created using a study-specific FORTRAN program to understand the relationships among items in the piles created by the children. The proximity matrix for the 71 food items was a symmetric 71×71 matrix of co-occurrence inputs. For example, the value of 124 in column (C) 11, row (R) 12 indicated that 124 of 149 total children put chocolate cupcake (C11) and brownie (R12) in the same pile. In contrast, the value of 1 in C11 and R69 indicated only one of 149 children put chocolate cupcake (C1) and popcorn (R2) in the same pile, suggesting that nearly all children perceived chocolate cupcake and popcorn as not similar. Robinson matrices (Figure) provide a clustering procedure with general restrictions (20). Cutpoints (19,21) defined the levels from most similar to the least similar: (a) the most similar food items (values \geq 3), square icon in the Figure; (b) high to moderately similar food items (values \geq 1), blank cells. A complete discussion of (anti) Robinson matrices may be found elsewhere (19,21). The most common names that the children used to name the corresponding food piles were used for naming the clusters resulting from the Robinson matrix analyses.

RESULTS AND DISCUSSION

A total of 152 children were recruited for the study and completed the grains card sort. Three children were excluded because of missing data. In the sample of 149 children included in data analysis, 57% were female, 89.3% were predominantly English-speaking, 43.0% were Hispanic; and 56.4% had a normal BMI. For 51.7%, family income was more than \$60,000/ year; 52.3% had a college graduate or higher education in the home. Subjects were approximately equally distributed across the ages 8 to 13 years old (Table 2). Children created a mean±standard deviation of 8.3 ± 3.8 piles with 8.6 ± 9.1 cards per pile. Children from lower-income households had significantly more piles (\overline{x} =10.3±4.2) than children from medium-income (\overline{x} =8.1±2.9) or highest-income (\overline{x} =8.2±3.7) households (F (2,127)=6.37, *P*≤0.002). The mean number of piles significantly varied as a main effect across levels of highest household education (Table 2), but pairwise comparisons showed no significant differences. No other significant differences were detected.

The correlations between the number of piles used in this card sort with the number of piles in the first card sort (foods from 18 diverse professionally identified food categories) (11), second card sort (foods from 14 professionally identified complex food categories) (12), third card sort (fruit), and fourth card sort (vegetables) were 0.47, 0.46, 0.47, and 0.50, respectively (13). All correlations were significant (P < 0.01).

The Robinson matrix analysis for all children (Figure) accounted for 89.3% of the variance in child categorization of foods, so no further analyses of the residual matrices were done. Seven overlapping clusters were identified. "Crackers/taxonomic-professional" was the first cluster and included: A.25 snack crackers, H.1 popcorn, A.2 animal crackers, and A.20 graham crackers. The largest cluster labeled "bread/taxonomic-professional" (considering the most commonly used names by the children) was from G.1 french toast to B.7 corn tortilla. The clusters in the Figure were successively labeled crackers, desserts, sweets, breakfast breads, breads, cereals, and pasta/noodles/rice. This analysis revealed that perceived cracker items were least similar to pasta-noodles-rice. No substantial differences in Robinson clustering were detected when conducted within subcategories for each of the demographic characteristics. No clusters reflected differences between whole- and refined-grain foods.

Food cards were the unit of analysis in Table 1. There were 429 first-level pile names given by the children that were coded into 120 second-level codes, which were in turn categorized into the 11 third-level categories. Children categorized most of the cards into the "taxonomicprofessional" (34.5%) and "script-schema" (26.1%) third-level categories (bottom row in Table 1). Foods from the professional categories that were most commonly (modal response) categorized into the "taxonomic-professional" conceptual category were breads, rolls and tortillas (53.6%), rice and other grains (44.3%), cereals and energy bars (30.9%), baked goods (25.5%), frozen foods and food mixtures (24.8%), and pasta, noodles, and spaghetti (24.5%). The foods that were most commonly categorized into the "script-schema" conceptual categories included pancakes, waffles, flapjacks (40.1%), cereals and energy bars (38.3%), salty snacks (38.3%), and baked goods (32.5%).

Children age 8 to 13 years old categorized 71 foods into six clusters with the Robinson matrix procedure (Figure) with no substantial differences in clustering across demographic characteristics. The high percentage of variance accounted for by the clusters suggested that children within this age think about and categorize foods in a similar way. Thereby these groupings should be useful in a computerized 24-hour dietary recall to facilitate children's search for grain foods. Alternatively, there was substantial variability among the names that children gave to the piles (ie, 120 second-level names). A considerable number of foods were placed in the "do not know," "not sure," or "not matched" categories, which can be problematic for dietary assessment. In completing a computerized 24-hour recall, however, children who search for categories for the foods they themselves consumed should know the foods and, therefore, not be using these categories.

The number of categories varied by family income and highest household education. Ordinarily, a larger number of categories would be considered an indicator of cognitive complexity (22), which is considered an aspect of personal style or personality. It is possible that living in lower income or educational environments forces children to develop more detailed ways of categorizing foods. This could be due to lower-income children eating more lower-cost grain foods (23). Lower-income children were more likely to use food characteristics and thematic type categories, suggesting they were somewhat more likely to use the cognitively simpler schemas, which may reflect lower educational attainment. Further research will need to clarify this.

Alternatively, context appears to influence categorizing of foods. Several food items (ie, brownies, cookies, chocolate cupcake, cake, doughnut, pan dulce, pancakes, and waffles) were grouped in different categories in this and the first card sort (11). In the first card sort with diverse foods, brownies, cookies, chocolate cupcake, cake, dough-nut, and pan dulce were most commonly classified in the snack/script category, but in this grains card sort, brownies, chocolate cupcake, and cake were classified in the dessert/script category; cookies were classified in the crackers/taxonomic-professional, and doughnut and pan dulce were mostly classified in the sweets/taxonomic-professional category. Similar differences in classifying the same foods across different card sorts were seen with the tortilla, cereal, granola bar, rice, spaghetti, bagel, pancake, and waffle food items. These suggest children identified the same food items in different categories depending on the context. Thus, the same food item may need to be listed in multiple food categories to facilitate their being found in a 24-hour dietary recall.

As in other research (24), most children placed foods in taxonomic-professional or script categories. Using taxonomic-professional type categories suggests that many 8-to 13-year-old children tended to categorize foods within *Dietary Guidelines for Americans 2005*-type categories, but they used diverse category labels which did not correspond precisely to the 2005 Dietary Guidelines categories (25). This variability within the taxonomic categories suggests that children lacked a detailed knowledge of nutrition or 2005 Dietary Guidelines concepts. More consistency in use of food categories would be expected if children received more nutrition education. Common use of script categories suggests there is a cultural consensus about which foods are commonly eaten at specific meals.

Creating a computerized children's 24-hour dietary recall program would seem to benefit from using child-generated groups of foods that would include mostly taxonomic-professional and script categories. Redundant placement of foods in multiple categories will be necessary to accommodate the findings in Table 1. Research is needed to assess the accuracy and speed of categorization of foods by children using the professional categories vs the child categories.

Limitations of this study include small sample size for some of the ethnic/language subgroups that could have influenced the lack of differences in categorization by demographic characteristics. This was not a representative sampling of children, which means the findings might have been different with other children. The sampling was limited to 8- to 13-year-old children: we do not know how younger or older children would have categorized these foods. We used a relatively small sample of commonly eaten grain foods; the findings might be different with other grain foods.

CONCLUSIONS

Children aged 8 to 13 years old categorized grain foods in consistent ways, but with diverse category labels. Using these categories in a computerized 24-hour dietary recall for children should provide a framework that children better understand, thereby leading to quicker and more accurate dietary assessment.

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Figure.

Clusters derived from Robinson Matrices. Items within boxes identify clusters of foods determined by the Robinson matrix method. Cluster names reflect those used by children. General Mills (Golden Valley, MN): Cheerios, Cinnamon Toast Crunch, Lucky Charms, and Pop-Tarts. Kellogg's (Battle Creek, Ml): Frosted Mini Wheats, Rice Krispies, Rice Krispies Treats. Kraft Foods (Northfield, IL): Fig Newtons, Grape-Nuts.

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Frequencies and percentages of child food category labels by the original professional category sources of the foods and the third level Table 1 conceptual categories

	Evalua Prefere	utive- inces ^a	Specific Item	$\mathbf{F}^{\mathrm{ood}}$	Food Characteris	ticsb	Script-Sche	ma ^{ac}	Thematic Complement Relationshi	ary: p ^c	Food Preparation	Et .	ľaxonomic [.] hnic/Places	64 al	oal/Have ^unction:	Eva H Perc	luative- ealth eption ⁶	Taxone Profess	omic ional
onal grouping	u	%	u	%	u	%	u	%	u	%	n %		u	%	° u		n %	u	e,
l goods	58.0	1.4	106.0	2.6	413.0	9.6	1,351.0	32.5	217.0	5.2	19.0 0.	5	47.0	Ξ.	0.0	0 224	.0 5.4	1,059.0	25.

	Evalu Prefer	ative- ences ^a	Specific Item	Food	Food Characteristi	ics ^b S	cript-Scher	na ^{ac} C	Thematic Jomplement Relationshi	- tary: ip ^c F	ood Preparat	tion ^c E	Taxonomi thnic/Place	esct a	Goal/Hav Function	e E Fe	'aluativ Health rceptior	e- Dro	xonomic- fessional ^f	Nutrie Composi	nt tionf	Don't Kr Not Su Not Not Match	low, re, ed
Professional groupin	ے م	%	=	%	=	%	=	%	=	%	-	%	=	%	u	%	п	%	n %	n	%	u	%
A. Baked goods	58.0	1.4	106.0	2.6	413.0	9.9	1,351.0	32.5	217.0	5.2	19.0	0.5	47.0	1.1	0.0	0.0	24.0 5	.4 1,0	59.0 25.5	39.0	0.9	620.0	14.9
B. Breads, rolls and tortillas	31.0	1.0	110.0	3.7	103.0	3.5	322.0	10.8	152.0	5.1	12.0	0.4	23.0	0.8	0.0	0.0	57.0 2	.3 1,59	92.0 53.6	26.0	0.9	531.0	17.9
C. Cereals and the cg	19.0	1.2	20.0	1.2	91.0	5.6	626.0	38.3	70.0	4.3	2.0	0.1	15.0	0.9	0.0	0.0	58.0 3	.5 5()5.0 30.9	24.0	1.5	204.0	12.5
E. Frozen foods food mixture	3.0	2.0	5.4	5.4	4.0	2.7	19.0	12.8	9.0	6.0	0.0	0.0	1.0	0.7	2.0		4.0 2	L	37.0 24.8	1.0	0.7	61.0	40.9
F. Pancakes, whitles, flapjacks	4.0	0.0	28.0	6.3	26.0	5.9	178.0	40.1	28.0	6.3	7.0	1.6	3.0	0.7	0.0	0.0	10.0 2	.3)5.0 23.6	4.0	0.9	51.0	11.5
G. Pasta, noodes, and spaghetti	3.0	1.0	55.0	18.5	7.0	2.3	41.0	13.8	24.0	8.1	1.0	0.3	4.0	1.3	2.0 (7.0	6.0 2	0	73.0 24.5	3.0	1.0	79.0	26.5
H. Rice and other grain	s 4.0	0.7	3.0	0.5	19.0	3.2	105.0	17.6	6.0	1.0	3.0	0.5	10.0	1.7	3.0 (5.(15.0 2	.5 20	54.0 44.3	4.0	0.7	160.0	26.8
I. Salty snackser	4.0	1.3	11.0	3.7	16.0	5.4	114.0	38.3	7.0	2.3	0.0	0.0	4.0	1.3	0.0	0.0	23.0 7	Ľ	5.0 1.7	5.0	1.7	109.0	36.6
Total	126.0	1.2	341.0	3.2	679.0	6.4	2,756.0	26.1	513.0	4.9	44.0	0.4	107.0	1.0	7.0 (.1 4	07.0 3	.9 3,6	40.0 34.5	106.0	1.0	,815.0	17.2
a Evaluative-Drefe	rences eq	incentri	juussesse u	ent of fo	and nreference	a																	

Evaluating-Freterences: egocentric assessment of food preference.

(eg. cereatend milk, peanut butter and jelly); Food Preparation: eg. baked, frozen; Taxonomic-Ethnic/Places: eg. Mexican, Chinese, cafeteria. d Goal/Hate a Function: foods have a function (eg. extras, add-ons). e Evaluative-Health Perception: requires some knowledge of the health effects of foods.

f Requires some knowledge of professional groups: Taxonomic-Professional: based on common properties (eg, beverages, grains); Nutrient Composition: Macronutrient or micronutrient content.

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Table 2

Distribution of the sample, and the mean and standard deviation of the number of piles, across demographic categories

Characteristic	n	%	Mean±standard deviation
Total	149	100	8.3±3.8
Sex			
Male	64	43.0	7.7±3.9
Female	85	57.0	8.7±3.7
Age (y)			
8	23	15.4	9.2±4.6
9	24	16.1	9.2±4.3
10	33	22.1	7.6±3.2
11	26	17.4	8.0±4.1
12	16	10.7	9.1 ±3.7
13	27	18.1	7.3±3.0
Language spoken			
English	133	89.3	8.2±4.0
Spanish	16	10.7	9.1±2.4
Race/ethnicity			
White	47	31.5	7.8±3.2
African American	36	24.2	7.8±4.4
Hispanic	64	43.0	9.0±3.8
Other ^a	2	1.3	6.0±5.7
Obesity index			
Normal (BMI ^b %<85%)	84	56.4	8.5±3.8
At risk (85% <bmi%<95%)< td=""><td>28</td><td>18.8</td><td>8.5±4.5</td></bmi%<95%)<>	28	18.8	8.5±4.5
Overweight (BMI%≥95%)	36	24.2	7.6±3.4
Missing ^a	1	0.7	$5.0\pm NA^{C}$
Annual household income ^d			
<\$20.000	22	14.8	11.2±4.6
\$20,000-\$59,000	31	20.8	8.1 ±2.9
>\$60,000	77	51.7	8.2±3.7
Missing ^a	19	12.8	5.5±2.5
Highest household education ^e			
High school graduate or less	33	22.1	10.3±4.2
Some college/technical school	22	14.8	7.6±3.8
College graduate	78	52.3	8.2±3.4
Missing ^a	16	10.7	5.4±2.6

^aMissing category and "other" race/ethnicity not included in testing differences among number of piles.

^bBMI=body mass index.

^cNA=not applicable.

dSignificant effect [F(2,127)=6.37, P=0.002] for household income, post hoc revealed significant (P<0.0167) difference between <\$20,000 and both higher income categories.

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 e Significant effect for highest household education [F(2,132)=4.57, P=0.012]; however, post hoc tests yielded no significant (P<0.0167) pairwise comparisons.