Improving Nutrition Rankings for Food Banks

by

Justin Robert O'Driscoll
Bachelor of Arts in Supply Chain Management, Michigan State University, 2009

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Signature of Author: ____
Department of Supply Chain Management
May 10, 2024

Certified by: ____
Dr. Jarrod Goentzel
Director, MIT Humanitarian Supply Chain Lab
Capstone Advisor

Accepted by: ____
Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

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ABSTRACT

Food insecurity is a major concern for many Americans. Food banks and food pantries strive to provide enough food to satisfy the needs of people suffering from food insecurity. These organizations are also trying to distribute healthy food, not just meet the caloric intake necessary to sustain the community. The Mid-Ohio Food Collective (MOFC) is a food bank outside of Columbus, Ohio that was interested in measuring the healthfulness of their inventory in a context that could be communicated to those outside of the hunger relief system. Specifically, they wanted to use a scoring system called the Healthy Eating Index (HEI), which is used by healthcare professionals. The healthcare industry wants to alleviate certain long-term preventable diseases, like diabetes, by teaming with food banks and other organizations to provide healthy food options as a preventative measure. HEI is a 0-100 measure of the nutritional quality of a set of food, with higher scores being healthier. Using a subset of the MOFC inventory, I used Microsoft Excel and Python to provide the food bank with an HEI score that they could communicate with healthcare providers to show they are distributing healthy food to the food pantries and to other entities they serve which in turn distribute food to individual clients. The subset of the MOFC inventory had a score of 80.62 out of 100. While this score represented only a subset of their inventory, it was a promising start, as MOFC can track scores and make changes to their purchasing decisions to raise scores over time. Though the process of producing the score is not fully automated, it is generalizable and can be performed for other entities in the hunger relief system, allowing them to demonstrate the healthfulness of the products they distribute as well.

Capstone Advisor: Jarrod Goentzel
Title: Director, MIT Humanitarian Supply Chain Lab

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1. INTRODUCTION

Food insecurity is a serious concern in America. Roughly 10.2% of Americans experienced food insecurity in 2021 (USDA ERS). “The US Department of Agriculture’s (USDA) definition of food insecurity”, which has been adopted by Feeding America, “is a lack of consistent access to enough food for every person in a household to live an active, healthy life” (Feeding America). Government and non-profit organizations, like Feeding America, play a key role in addressing food insecurity in America. Non-profits operate networks of food banks, food pantries and other food assistance programs to serve those in need. A food bank is a place where food is stored and distributed for free or at very low cost. Food banks act as distribution centers providing goods to food pantries and food assistance programs, which in turn serve clients. To serve a variety of pantries and programs with different types of storage, capacity and client needs, food banks must make inventory decisions that balance these factors against a desire to provide healthy food options to the community.

1.1 Food As Medicine

A growing movement called Food As Medicine, sometimes referred to as Food Is Medicine, attempts to provide healthy food and education, with a focus on reducing food insecurity and complications from preventable chronic diseases like diabetes. Some of the practices include medically tailored meals, nutrition education for doctors, and produce prescriptions (Food is Medicine). Produce prescriptions are referrals for healthy food prescribed by a healthcare professional or insurance company (National Produce Prescription Collaborative). The motivation of these interventions is to lessen the burden on the American healthcare system by making people healthier overall, thus avoiding trips to emergency rooms and other medical facilities for care. It is estimated that these preventative measures could save $39.6 billion in healthcare costs over a lifetime of treatment for 6.5 million people who suffer from diabetes and food insecurity (Journal of the American Heart Association). Produce prescriptions could be filled by food pantries with the costs covered under government programs like Medicaid.

1.2 Mid-Ohio Food Collective

The Mid-Ohio Food Collective (MOFC) is a food bank outside of Columbus, Ohio that serves 20 surrounding counties. MOFC was interested in measuring the healthfulness of their inventory via a common ranking tool. In addition to the benefits described above that a common measurement would offer MOFC for communicating with medical stakeholders, MOFC wanted to understand how to influence scores with operational decisions. The ability to score the MOFC inventory is reliant on how inventory data are captured, and MOFC is currently changing this process. They do not have traditional

SKUs; instead, a new SKU is created every time a product is received. That will change later this year as they move to a new ERP in which they are also planning to use Universal Product Code (UPC) data. This capstone focuses on this future state and maps UPC data to the necessary nutrition database to calculate scores, allowing MOFC to apply it once their ERP transition is complete.

The first goal of applying a nutrition scoring metric to MOFC inventory was to help MOFC communicate more effectively with healthcare professionals. According to Amy Headings, the Director of Research and Nutrition at MOFC, there is a perception by many that the food in the charitable food system is unhealthy. Showing that food banks do provide nutritious options via a commonly accepted measurement would help dispel that perception (A. Headings, personal communication, November 22, 2023). The second goal was to identify the operational factors that influence the score and use that information to increase the healthfulness of the MOFC inventory. In addition to these MOFC goals, because the method uses UPC data, it should be possible to use this model at other food banks as well.

2. STATE OF THE PRACTICE

MOFC expressed an interest in applying the USDA Health Eating Index (HEI) to their inventory as a way to better communicate with stakeholders outside of the food bank space. They currently use a different health scoring system, the Healthy Eating Research (HER) guidelines. HER was developed specifically for food banks to assist workers in choosing healthier options for their inventory. While this may seem advantageous, it makes communication and comparison with non-food bank entities difficult, specifically with healthcare programs and providers, who use different metrics to assess healthfulness and guide medical decisions.

2.1 Healthy Eating Index

The Healthy Eating Index (Healthy Eating Index [HEI]) is a 0 to 100 measure of quality of diet. Traditionally, the HEI has been applied to an individual's food consumption as measured by food logs in periods of 24 to 48 hours (Healthy eating index [HEI]). Though a score of 100 is considered the goal, according to food log studies the average score for Americans is only 58 (Healthy eating index [HEI]). The HEI includes 13 components that reflect the key recommendations in the Dietary Guidelines for Americans, a collaboration between USDA and the Department of Health and Human Services. The 13 components in the HEI are divided into adequacy and moderation components, as noted in Table 1. The adequacy components are foods like fruits, vegetables, and whole grains. For these foods, higher consumption is encouraged and leads to higher scores. For example, eating at least 1.1 cups of vegetables per 1,000 kcals would give the maximum score of 5. The moderation components are sodium, refined grains, added sugars and fatty acids. Portions in this section are scored as an inverse, meaning the lower the component the higher the score. For example, if a food has little to no added sugar it will score closer to the maximum of 10 on the scale. Fatty acids and added sugar are measured as percentages of the total calories of all the food being scored, rather than cup or gram equivalents like the other categories. "A higher HEI score has been associated with a lower risk of chronic diseases, such as coronary artery disease, and overall mortality" (Scientific Reports 14, no. 1, February 12, 2024).

Table 1
Healthy Eating Index Components and Scoring Standards

Component	Maximum points	Standard for maximum score	Standard for minimum score of zero
		HEI-2020 Applies to ages 2 and over	
Adequacy Components			
Total Fruits[b]	5	≥ 0.8 cup equiv. per 1,000 kcal	No Fruit
Whole Fruits[c]	5	≥ 0.4 cup equiv. per 1,000 kcal	No Whole Fruit
Total Vegetables[d]	5	≥ 1.1 cup equiv. per 1,000 kcal	No Vegetables
Greens and Beans	5	≥ 0.2 cup equiv. per 1,000 kcal	No Dark Green Vegetables or Legumes
Whole Grains	10	≥ 1.5 oz equiv. per 1,000 kcal	No Whole Grains
Dairy[e]	10	≥ 1.3 cup equiv. per 1,000 kcal	No Dairy
Total Protein Foods[d]	5	≥ 2.5 oz equiv. per 1,000 kcal	No Protein Foods
Seafood and Plant Proteins[f]	5	≥ 0.8 oz equiv. per 1,000 kcal	No Seafood or Plant Proteins
Fatty Acids[g]	10	(PUFAs[h] + MUFAs[i])/SFAs[j] ≥ 2.5	(PUFAs + MUFAs)/SFAs ≤ 1.2
Moderation Components			
Refined Grains	10	≤ 1.8 oz equiv. per 1,000 kcal	≥ 4.3 oz equiv. per 1,000 kcal
Sodium	10	≤ 1.1 grams per 1,000 kcal	≥ 2.0 grams per 1,000 kcal
Added Sugars	10	< 6.5% of energy	≥ 26% of energy
Fatty Acids	10	≤ 8% of energy	≥ 16% of energy

Note. From U.S. Department of Agriculture. Food and Nutrition Service (2020).
https://www.fns.usda.gov/cnpp/healthy-eating-index-hei

2.2 HER Guidelines

While the end goal of food banks is having healthy food options available for clients, there have been many approaches to reaching that goal. The HER guidelines are the most prevalent in the Feeding America network of 200 food banks and are being utilized by more than 100 across the country (Food Bank News, August 18, 2023). HER uses a green, yellow and red coding system to identify foods that should be chosen often, sometimes or rarely (Journal of the Academy of Nutrition and Dietetics, 2020). HER primarily uses saturated fat, sodium and added sugar to rank foods. Foods are categorized by the lowest ranking nutrient. This means that if the level of fat, sodium, or sugar in an item falls in the red, or choose rarely category, then that particular food also falls into that category. The HER system was not designed to be client facing but ultimately has become so to help clients make healthier choices (A. Headings, personal communication, November 22, 2023.). Table 2 shows the ranking for a variety of foods.

Table 2

HER Guidelines

Category	Choose Often	Choose Sometimes	Choose Rarely
Fruits and Vegetables	Fresh, frozen and canned fruits and vegetables with no added sugar or sodium; low sodium vegetables; fruit canned in 100% juice or in water	100% juice; fruit canned in light syrup; canned vegetables; plain dried fruit	Dried fruit with sugar added; fruit canned in heavy syrup; tomato sauce with added sugar; vegetables canned with high sodium
Grains	Whole grains (quinoa, brown rice, barley); whole wheat pasta; whole grain breads; whole grain cereal with ≤6 grams added sugar; plain oatmeal	Refined grain products (white breads, pasta, rice); oatmeal with added sugar; whole or non-whole grain cereal with 7-11 g of total or added sugar	Rice and pasta with salt-based seasoning mixes; whole or non-whole grain cereal with ≥12 g of sugar
Protein	Dried beans; low-sodium canned beans; some nut butters; nuts; fresh poultry; fish; eggs; tofu; low-sodium canned tuna; canned salmon	Canned beans; baked beans; some nut butters; regular canned fish; pork	Refried beans; deli meat; sausage; bacon; most red meat; breaded chicken
Dairy	Fat-free or low-fat unsweetened yogurt; skim, 1% and 2% milk; fat-free and reduced fat cheeses; light sour cream	Some reduced fat or whole milk cheeses; cottage cheese; whipped cream cheese; whole milk; full-fat sour cream; some low-fat flavored milks; low-fat flavored yogurts	Full-fat cheese and cream cheese; some low-fat and full-fat flavored milks; some flavored yogurts
Non-Dairy Alternatives	Unsweetened almond, rice, cashew, oat and pea milk; unsweetened soy, almond, rice, cashew and oat milk yogurts; some plain non-dairy alternative products with ≤ 6 g of added sugar	Plant-based cheeses; some flavored soymilks; plain and flavored soy, almond, rice, cashew and oat milk yogurts	Plant-based cream cheese; flavored soy, almond, rice, cashew and oat milk yogurts; plain and flavored coconut milk; flavored soy, almond, rice, cashew, and oat milk
Beverages	Plain water; flavored and unflavored sparkling water; plain coffee; unsweetened tea	Diet soft drinks; diet iced teas; sugar free energy drinks; sparkling water with sodium or added sugar; coconut water	Sweetened energy drinks; sports drinks; regular sodas; non-100% juice drinks with added sugar
Mixed Dishes*	Variability by product formulation is more substantial than other categories	Variability by product formulation is more substantial than other categories	Variability by product formulation is more substantial than other categories
Processed/ Packaged Snacks	None	Plain popcorn; whole wheat crackers; green pea snack crisps; rice cakes; unsalted whole grain pretzels; some snack bars	Pretzels; cheese crackers; potato chips; granola and other snack bars; flavored popcorn
Desserts	None	None	All desserts
Condiments and Cooking Staples	Not ranked		
Miscellaneous products	Not ranked		

Note. HER Guidelines from https://healthyeatingresearch.org/wpcontent/uploads/2020/02/her-food-bank_FINAL.pdf

2.3 HEI and Food Banks

In contrast to HER, which was designed for food banks, HEI was designed to be used on an individual basis, scoring the healthfulness of a person's daily food intake. Although HEI was designed to be used on data captured in the food logs of individuals, there are many other potential applications using larger data sets instead, ranging from restaurant inventory to the national food supply (Research Uses of the Healthy Eating Index). For example, the work of Nanney et al. (2016) at the University of Minnesota applied the HEI to the hunger relief system i.e. food banks and food pantries. To do this, the researchers scraped invoices for 269 food pantries receiving goods from two food banks in the Minneapolis area and first mapped the results to the Food and Nutrient Database of Dietary Studies (FNDDS), which is "a database that provides the nutrient values for foods and beverages" (FNDDS). Mapping to the FNDDS was the first step in being able to calculate the HEI. They then used this mapping to calculate HEI scores for each of the pantry invoices. Nanney et al. (2016) set out to show that calculating the HEI on all items received by food pantries was possible. While they were able to achieve their goal, the study was not without limitations. A challenge of their work was how time-consuming the mapping process is, especially when there are always new products in the invoices that need to be matched to the FNDDS. Two dietitians were responsible for all mapping, one to do the initial matching and a second to check this work, by testing a 10% sample (Public Health Nutrition, 2016).

Multiple follow-up studies were done to streamline this mapping process using food categories instead of individual items. For example, King et al. (2016) explored using the 33 common categories used by food banks in the Feeding America system in the Hunger Relief Nutrition Index. Caspi et al. (2018) followed up this work by reducing the number of categories to 13 and using 31 subcategories as percentages of the main category in the Food Assortment Scoring Tool. While much easier to implement, the results were not exact matches to the HEI. The Hunger Relief Nutrition Index had a correlation coefficient of 0.68 when compared to HEI. The Food Assortment Scoring Tool had a correlation coefficient of 0.75 when compared to HEI. According to Akoglu (2018), "[t]he relationship (or the correlation) between the two variables is denoted by the letter r and quantified with a number, which varies between −1 and +1. Zero means there is no correlation, where 1 means a complete or perfect correlation." While these are moderate to strongly correlated with HEI, MOFC did not specify that a proxy system would be acceptable, so I focused on the direct application of the HEI to MOFC inventory.

3. DATA & METHODOLOGY

The focus of this capstone was on developing a process to calculate HEI scores for MOFC using their inventory data and suggesting purchasing and inventory changes based on HEI to improve scores. MOFC sent a list of UPC codes and produce items that they had purchased, as well as the quantity and weight of each, to run an initial calculation. A snapshot of purchased inventory was used because the UPC codes can be scanned and easily tracked and because this is the segment of inventory that MOFC has the most direct control over.

3.1 Nutrition Databases

The first step in calculating the HEI for MOFC was mapping individual items to the FNDDS and Food Patterns Equivalent Database (FPED). The combination of data from the FNDDS and FPED give us the nutritional information needed to calculate HEI. There are roughly 7,000 food options in the FNDDS ranging from raw fruit to many varieties of pizza. The FNDDS contains calories, sodium, saturated, monounsaturated, and polyunsaturated fats; but the rest of the nutrient information comes from the FPED. These 5 columns must be merged into FPED in order to make the HEI calculation. FNDDS and FPED include the same list of items but contain different attributes of the items. FNDDS primarily focuses on vitamin and mineral content, like vitamin B or iron, while FPED contains 37 nutritional categories like whole fruit, legumes, added sugar, and protein.

The information contained in FPED and FNDDS is for the whole item and not its components. This is because the HEI was designed to be used on food logs, so using the whole item makes more sense than adding individual ingredients because someone will track consumption of pepperoni pizza rather than consumption of cheese, marinara sauce, bread, and pepperoni. Further, the FPED includes calorie and nutrition information based on 100-gram servings of each food, while the HEI is based on caloric density of 1,000 kcal. Because of the scale difference the weight of the food must be used as a multiplier for all nutritional categories to properly balance the number of calories each food item has as a percentage of the total dataset of food being looked at. I did this work in Microsoft Excel and then summed up the total amount for each category (e.g. total fruit, whole grains, etc). The HEI was then calculated by taking the totals of each nutritional category in FPED and FNDDS from the Excel sheet and running a macro in Statistical Analysis System (SAS) offered by the National Cancer Institute. The macro combines and sums the FNDDS and FPED categories into the 13 adequacy and moderation components for HEI listed in Table 1. For instance, the component for seafood and plant protein is a combination of columns for seafood, nuts, soy, and legumes from the FPED.

3.2 Testing the Macro

Prior to receiving data from MOFC, I created a test data set to confirm that the National Cancer Institute SAS macro worked as expected. I designed the test data set to compare fictional grocery baskets with a set of six similar items, one set being notably healthier than the other, in order to see how the HEI scores were impacted. The grocery basket idea came from a desire to simplify the problem and was consistent with the record of HEI being calculated on food logs. For example, I chose fresh peaches and raw tuna for the healthier basket and canned peaches and canned tuna for the less healthy basket. The HEI scores were 94.8 for the Perishables basket in Table 3 and 54.7 for the Shelf Stable basket in Table 4. Combining them resulted in a score of 78.3. They were combined to see how each basket would affect a total score and whether they would be equally weighted. That was not the case: the Perishables basket carried more weight and raised the total score beyond the mean of the two.

Table 3
Grocery Basket 1, Perishables

FOODCODE	DESCRIPTION
11114320	Milk, lactose free, fat free (skim)
26153100	Tuna, fresh, raw
51300110	Bread, whole wheat
63135010	Peach, raw
75101800	Green beans, raw
63105010	Avocado, raw

Table 4
Grocery Basket 2, Shelf Stable

FOODCODE	DESCRIPTION
26155110	Tuna, canned, NS as to oil or water pack
42202000	Peanut butter
63135140	Peach, canned, in syrup
75205131	Green beans, canned, reduced sodium, cooked with oil
14650160	Alfredo sauce
56130000	Pasta, cooked

Here is an example of the process using canned peaches from the Shelf Stable basket. The calculation for total fruit in the HEI is shown below. A can contains 432.33 grams, but because all the nutrient components are given by 100 grams in the FPED, I divided the can weight in grams by 100 to get a multiplier of 4.3233. The total fruit category in the FPED has a multiplication factor for canned peaches of 0.26. This multiplication factor is the cup equivalent for total fruit, meaning for every 100 grams of canned peaches there are 0.26 cups of total fruit included in the basket. The HEI is based on cup equivalents per 1,000 calories so this is converting the initial weight in grams to a volume measurement in cups. I then multiplied the 0.26 by 4.3233 to get a total of 1.124058, which is f_total in the equation. There is no other fruit in the basket. The total calories for the Shelf Stable basket are 9,024.085, which is kcal in the formula. The calculation for FRTDEN equals 0.12456. Inputting that into the next line means Total Fruit is 0.7785 out of a maximum of 5.

Table 5

Variables to Calculate Total Fruit

Variable	Description
g	Total Grams per Food Item
f	Cup Equivalents per 100 Grams
kcal	Calories
f_total	Total Cup Equivalents of Fruit
FRTDEN	Density of Total Fruit per 1000 kcal
Total Fruit	Category Score for Total Fruit in the HEI

f_total = (g / 100) * f

FRTDEN = f_total / (kcal / 1000)

Total Fruit = 5 * (FRTDEN / 0.8)

f_total = (432.33 / 100) * 0.26

= 1.124058

kcal = 9024.085

FRTDEN = 1.124058/ (9024.085 / 1000)

= 1.124058 / 9.024085

= 0.124561

Total Fruit = 5 * (0.124561 / 0.8)

= 0.7785

Total Fruit is one of the 13 categories listed in Table 1. Some foods qualify for more than one category, such as canned peaches, which also produce an output for Whole Fruits. The category Whole Fruits is comprised of whole or cut versions of citrus, melons, and berries (f_citmlb) and whole or cut fruits excluding citrus, melons, and berries (f_other). In this case, the multiplier for f_citmlb is zero and f_other is 0.26. They were added together to get w in Table 6. The calculation for Whole Fruits using the same can of peaches as before is below.

Table 6

Variables to Calculate Whole Fruit

Variable	**Description**
g	Total Grams per Item
w	Cup Equivalents per 100 Grams
kcal	Calories
fwholefrt	Total Cup Equivalent of Fruit
WHFRDEN	Density of Whole Fruit per 1000 kcal
Whole Fruit	Category Score for Whole Fruit in the HEI

fwholefrt = (g / 100) * w

WHFRDEN = fwholefrt / (kcal / 1000)

Whole Fruit = 5 * (WHFRDEN / 0.4)

fwholefrt = (432.33 / 100) * 0.26

= 1.124058

Kcal = 9024.085

WHFRDEN = 1.124058 * (9024.085 / 1000)

= 1.124058 / 9.024085

= 0.124561

Whole Fruit = 5 * (0.124561 / 0.4)

= 1.557

A similar calculation is done for each of the other 11 components of the HEI. Both Total Fruit and Whole Fruit were added together with the other 11 components to give the total score of 54.7 for the Shelf Stable basket.

SAS is a niche tool, so I thought it was best to convert the macro into Python to make it more accessible for MOFC. The Python code was written in Colab, which is free and only requires a Google account. I was able to run the Python code on the original test dataset and got the same scores, confirming that it works as intended. The complete code is located in Appendix A.

3.3 Data

Mapping MOFC's inventory list to the FNDDS is a time-consuming manual process but essential for calculating the HEI because each unique food item has different nutritional information. In order to test the application of HEI at MOFC, MOFC initially sent a list of 62 UPC codes, plus 19 fresh produce items to map. Three of the 62 were non-food items and two were deemed ingredients by the FNDDS and thus do not have nutrient information in the FPED (e.g. wheat flour). These five were disregarded. Most items in the FNDDS are generic so many of the items I mapped are not exact matches based on the branding. For instance, UPC code 10010700702309 is for Jolly Rancher Original Hard Candy. This is not in the FNDDS, so generic "hard candy" was chosen as the match. Most of the mapping was done based on the provided descriptions and the information available online for the UPC codes. I searched to find pictures of the items to confirm package type and match the appropriate descriptions to them. The initial list did not include quantities and weights of the items. While waiting for the official quantities from MOFC I used 40,000lbs as a placeholder weight for all items. MOFC said they often order in full truckloads and one full truckload is equal to 40,000lbs.

MOFC sent a second list of items received on another week, including quantities and weights. Some of the items included UPC information (e.g. consumer packaged goods) and others did not (e.g. dairy and produce). The full list of items for Dataset 1 and Dataset 2 are included in Appendix B. Dataset 2, representing one week of shipments received by MOFC, also included the quantity received in cases, the units per case, and the unit weight in either ounces, pounds, gallons, or dozens of eggs. There were three duplicate items on the list, according to the FNDDS code. Apples and white potatoes were each listed twice. Clementines and mandarins were both listed in the MOFC data but only clementines are available in the FNDDS, so one code was used for both. All quantities were multiplied to get a total weight. This weight was then converted into grams. For example, the first item on the list was garbanzo beans. There were 1,530 cases. Each case contained 24 units and each unit was 15 ounces. There are 28.3495 grams in an ounce. Multiplied together the total weight was 15,614,904.6 grams.

When calculating the HEI, information was pulled from both the FPED and FNDDS. I did Xlookups in Excel to merge the two based on the foodcode, which is the identification number used in both databases. I then brought the multipliers for calories, sodium, saturated, monounsaturated, and polyunsaturated fats from FNDDS into FPED. Then I took the MOFC list of inventory and used another Xlookup to create a filter in FPED for just those items and saved them to a new worksheet. I copied the headers for all the nutrient components, creating 41 new columns, and multiplied the total grams divided by 100 for each line item by the appropriate multiplier. The quantities were then summed and saved to a new worksheet. To sum the duplicate values and put the correct weights into the calculation, I used a pivot table.

4. RESULTS

Running the HEI for the initial dataset where full truckloads were used resulted in a score of 81.01, as seen below. These results are likely skewed due to the fact that many of the items in the data set would cube out, or reach the maximum volume of a container or truck, before reaching the maximum weight allowance. In that case, full truckloads would overestimate the amount of lighter items like a bag of potato chips.

```
TOTALVEG  GREEN_AND_BEAN  TOTALFRUIT  WHOLEFRUIT  WHOLEGRAIN  TOTALDAIRY
 3.709121       2.079215    3.711057         5.0    7.017065     3.06245

TOTPROT  SEAPLANT_PROT  FATTYACID  SODIUM  REFINEDGRAIN  TOTSATFAT
    5.0            5.0       10.0    10.0          10.0   9.891029

ADDSUG    TOTAL_SCORE
6.544483     81.01442
```

The HEI was then calculated on the second dataset where quantities and weights were included resulting in a score of 80.62. No whole grains were included in the data set, resulting in a zero out of 10 for the category, and dairy scored only 2.36 out of a possible 10. Saturated fat received a score of 8.26 out of 10. All other categories received the maximum score.

```
TOTALVEG  GREEN_AND_BEAN  TOTALFRUIT  WHOLEFRUIT  WHOLEGRAIN  TOTALDAIRY
   5.0               5.0         5.0         5.0         0.0    2.366474

TOTPROT  SEAPLANT_PROT  FATTYACID  SODIUM  REFINEDGRAIN  TOTSATFAT ADDSUG
  5.0              5.0       10.0    10.0          10.0   8.256224    10.0

TOTAL_SCORE
80.622697
```

I was curious whether removing vegetable oil, one of the items in the second dataset, would raise the score since it is a cooking accessory and not really a food. I assumed it was the reason for the less than perfect saturated fat score in the initial calculation. However, when I removed vegetable oil from the dataset and ran the code again, the score went down slightly to 79.30. The saturated fat score was at the maximum, but fatty acids and sodium had both decreased. Vegetable oil is calorically dense and, outside of the fat and oils categories, it does not offer any nutritional value, according to FPED. The added calories appear to skew the rest of the data.

```
TOTALVEG  GREEN_AND_BEAN  TOTALFRUIT  WHOLEFRUIT  WHOLEGRAIN  TOTALDAIRY
 5.0             5.0         5.0         5.0         0.0       3.612641

TOTPROT   SEAPLANT_PROT  FATTYACID    SODIUM  REFINEDGRAIN  TOTSATFAT
  5.0           5.0      9.68469    6.007553          10.0       10.0

ADDSUG  TOTAL_SCORE
10.0    79.304885
```

I believe this second dataset with a score of 80.623 is a good baseline for MOFC. Nanney et al. (2016) found that food pantry scores range from 28-82 with an average of 62.7. While purchasing is only a portion of their inventory, and this represents only one week of purchased goods, the score shows the healthfulness of the products they choose to order and distribute. They could also raise scores quite easily considering there were no whole grains included and only limited dairy products.

5. DISCUSSION

This project tested the process for applying a new measure of healthfulness to a food bank inventory at MOFC for a very small subset of the organization's inventory. This discussion covers possible ways to apply this process in the future as well as key considerations and limitations of extending the HEI scoring process for a food bank application.

Beyond this capstone, there are questions that need to be answered to make this a viable solution for MOFC. For example, can it be streamlined to include all items MOFC inventories throughout the year? Can the scores be easily incorporated into MOFC processes so they can track and focus on improving over time?

5.1 Recommendations

The ideal scenario for MOFC is to have a streamlined process to map their inventory to the HEI. My recommendation to run this calculation themselves is to export a list of items that have already been mapped to the FNDDS, with the weight of the inventory, from their ERP. They would pull this list into a merged FNDDS and FPED file, multiply out the nutrient components and save a separate totals sheet. They should use this sheet as the generic input for the Python code so they can set up a file path to read the same file for each time they run the HEI calculation on a set of items or their full inventory. There is an output file created each time the code is run so there is no need to save a unique file for every calculation. MOFC could then use the output files to track previous scores against the current score.

Tracking HEI scores consistently would allow MOFC to improve their inventory based on this measure of healthfulness. MOFC could make purchasing decisions based on their results. If they see consistently low scores in certain categories, for example whole grains, they can allocate more of their resources to that category as a means of raising the total score. Further, they would develop a better understanding of whether their inventory changes over time. For example, is there a seasonality aspect to them? Are scores higher from April to October because more fruits and vegetables are in season? These are the kind of questions MOFC could explore moving forward with consistent measurement of HEI scores for their inventory.

5.2 Concerns and Limitations

The concerns mentioned here are related to database issues encountered throughout the research process. MOFC was apprehensive about using FNDDS and FPED and would have preferred to use the Food Data Central (FDC) database instead because it contains many of the branded items they carry, eliminating having to use the closest equivalent and offering the exact nutrients of their inventory. However, FDC does not include information about the content of fruit, whole grains, vegetables, etc. that are critical to calculating the HEI. Therefore, we decided to continue using the FPED and FNDDS. One approach that could simplify the mapping process for MOFC is using 1World Sync to get the UPC data. 1World Sync is a subscription platform that provides detailed information and images for consumer packaged goods. For some of the UPC codes there was limited information available online. Using 1World Sync's database of products would speed up the process and provide more accuracy in the choices made. This would help alleviate some of the concerns MOFC had with using FNDDS and FPED.

One of the limitations of this study was using prepared foods from the FNDDS and FPED to match the MOFC inventory. Using prepared foods in the context of a food log, which is the original purpose of FNDDS and FPED, makes sense. However, evaluating the inventory of an organization like a food bank is less straight forward. This concern was brought up by Director of Research and Nutrition Amy Headings after my initial test data set used cooked pasta. The food bank does not store cooked pasta, but rather uncooked goods. Her concern was echoed in the research by Nanney et al. (2016) who noted that the food pantry they were evaluating had cake mix and the closest match in the FNDDS is a prepared cake without frosting. The sources I found all used the FNDDS as the nutrition database. According to the National Cancer Institute, it is not mandatory to use it to calculate HEI. There may be other nutrient databases to explore that more closely align with the food held by food banks and food pantries.

Another limitation was being able to calculate the HEI on only a small portion of the overall inventory. Given that donations are difficult to track and evaluate, it would be valuable to get consistent information, such as weekly or monthly purchases, over a year to get a more accurate view of the MOFC inventory.

5.3 Future Work

One recommendation as a follow up to this capstone would be to implement a machine learning model to automate the mapping process. To develop a classification model, it would be necessary to have a significant number of items, probably UPC codes, already mapped to the FNDDS and FPED to use as a training set. A Python library like fuzzywuzzy that compares text could be used to evaluate the similarity of the descriptions. After streamlining the mapping process it would be easier for MOFC to run the HEI on a variety of data sets. They could evaluate their entire inventory, the goods sent to specific food pantries, or even look at individual purchases at a pantry using point of sale data. The scores derived from any of these scenarios could not only influence purchasing and inventory decisions for MOFC but also communicate to healthcare professionals the healthfulness of the food they are distributing.

6. CONCLUSION

Food insecurity is a major issue throughout the United States. Food banks and food pantries are a critical part of the infrastructure to fight food insecurity. While meeting the nutritional needs of the at-risk population is a quantitative problem, a qualitative perspective should also be considered. It is the responsibility of food banks like the Mid-Ohio Food Collective to provide not only enough food to satisfy their clients but the right food.

Measuring the nutritional quality of their inventory is becoming more critical to the hunger relief system as they are being asked to collaborate with the healthcare industry to mitigate the effects of not only food insecurity but long-term preventable diseases like diabetes. It is important for these two industries to be able to communicate in the same terms to reach a shared goal.

The Healthy Eating Index is a way for food banks to effectively show the nutritional quality of their inventory to healthcare professionals. By tracking the inputs over time, it should be possible to improve scores and, therefore, increase the amount of healthy food distributed to those in need. Being able to show the food they distribute is healthy via a common measurement will help dispel misconceptions about the hunger relief system and promote greater confidence from the healthcare industry as they tackle nutrition related issues.

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APPENDIX A

```
import pandas as pd

import numpy as np

# Load the Totals totals

totals = pd.read_excel('Totals.xlsx')


# Calculate additional variables

totals['FWHOLEFRT'] = totals['F_CITMLB'] + totals['F_OTHER']

totals['MONOPOLY'] = totals['MFAT'] + totals['PFAT']

totals['VTOTALLEG'] = totals['V_TOTAL'] + totals['V_LEGUMES']

totals['VDRKGRLEG'] = totals['V_DRKGR'] + totals['V_LEGUMES']

totals['PFALLPROTLEG'] = totals['PF_MPS_TOTAL'] + totals['PF_EGGS'] + totals['PF_NUTSDS'] +
totals['PF_SOY'] + totals['PF_LEGUMES']

totals['PFSEAPLANTLEG'] = totals['PF_SEAFD_HI'] + totals['PF_SEAFD_LOW'] + totals['PF_NUTSDS'] +
totals['PF_SOY'] + totals['PF_LEGUMES']


# Group by USERNAME and USERID and calculate sums

totals_grouped = totals.groupby(['USERNAME']).agg({

    'KCAL': 'sum',

    'VTOTALLEG': 'sum',

    'VDRKGRLEG': 'sum',

    'F_TOTAL': 'sum',

    'FWHOLEFRT': 'sum',

    'G_WHOLE': 'sum',

    'D_TOTAL': 'sum',

    'PFALLPROTLEG': 'sum',

    'PFSEAPLANTLEG': 'sum',

    'MONOPOLY': 'sum',

    'SFAT': 'sum',
```

```
    'SODI': 'sum',
    'G_REFINED': 'sum',
    'ADD_SUGARS': 'sum'
}).reset_index()

def calculate_hei2015(indat, kcal, vtotalleg, vdrkgrleg, f_total, fwholefrt, g_whole, d_total,
                      pfallprotleg, pfseaplantleg, monopoly, satfat, sodium, g_refined, add_sugars, outdat):
    # Read the input totals
    totals = pd.read_csv(indat)

    # Calculate densities
    totals['VEGDEN'] = totals[vtotalleg] / (totals[kcal] / 1000)
    totals['TOTALVEG'] = 5 * (totals['VEGDEN'] / 1.1)
    totals.loc[totals['TOTALVEG'] > 5, 'TOTALVEG'] = 5
    totals.loc[totals['VEGDEN'] == 0, 'TOTALVEG'] = 0

    totals['GRBNDEN'] = totals[vdrkgrleg] / (totals[kcal] / 1000)
    totals['GREEN_AND_BEAN'] = 5 * (totals['GRBNDEN'] / 0.2)
    totals.loc[totals['GREEN_AND_BEAN'] > 5, 'GREEN_AND_BEAN'] = 5
    totals.loc[totals['GRBNDEN'] == 0, 'GREEN_AND_BEAN'] = 0

    totals['FRTDEN'] = totals[f_total] / (totals[kcal] / 1000)
    totals['TOTALFRUIT'] = 5 * (totals['FRTDEN'] / 0.8)
    totals.loc[totals['TOTALFRUIT'] > 5, 'TOTALFRUIT'] = 5
    totals.loc[totals['FRTDEN'] == 0, 'TOTALFRUIT'] = 0

    totals['WHFRDEN'] = totals[fwholefrt] / (totals[kcal] / 1000)
    totals['WHOLEFRUIT'] = 5 * (totals['WHFRDEN'] / 0.4)
    totals.loc[totals['WHOLEFRUIT'] > 5, 'WHOLEFRUIT'] = 5
```

```
totals.loc[totals['WHFRDEN'] == 0, 'WHOLEFRUIT'] = 0

totals['WGRNDEN'] = totals[g_whole] / (totals[kcal] / 1000)
totals['WHOLEGRAIN'] = 10 * (totals['WGRNDEN'] / 1.5)
totals.loc[totals['WHOLEGRAIN'] > 10, 'WHOLEGRAIN'] = 10
totals.loc[totals['WGRNDEN'] == 0, 'WHOLEGRAIN'] = 0

totals['DAIRYDEN'] = totals[d_total] / (totals[kcal] / 1000)
totals['TOTALDAIRY'] = 10 * (totals['DAIRYDEN'] / 1.3)
totals.loc[totals['TOTALDAIRY'] > 10, 'TOTALDAIRY'] = 10
totals.loc[totals['DAIRYDEN'] == 0, 'TOTALDAIRY'] = 0

totals['PROTDEN'] = totals[pfallprotleg] / (totals[kcal] / 1000)
totals['TOTPROT'] = 5 * (totals['PROTDEN'] / 2.5)
totals.loc[totals['TOTPROT'] > 5, 'TOTPROT'] = 5
totals.loc[totals['PROTDEN'] == 0, 'TOTPROT'] = 0

totals['SEAPLDEN'] = totals[pfseaplantleg] / (totals[kcal] / 1000)
totals['SEAPLANT_PROT'] = 5 * (totals['SEAPLDEN'] / 0.8)
totals.loc[totals['SEAPLANT_PROT'] > 5, 'SEAPLANT_PROT'] = 5
totals.loc[totals['SEAPLDEN'] == 0, 'SEAPLANT_PROT'] = 0

totals['FARATIO'] = totals[monopoly] / totals[satfat]
totals['FARMIN'] = 1.2
totals['FARMAX'] = 2.5
totals.loc[(totals['SFAT'] == 0) & (totals['MONOPOLY'] == 0), 'FATTYACID'] = 0
totals.loc[(totals['SFAT'] == 0) & (totals['MONOPOLY'] > 0), 'FATTYACID'] = 10
totals.loc[totals['FARATIO'] >= totals['FARMAX'], 'FATTYACID'] = 10
totals.loc[totals['FARATIO'] <= totals['FARMIN'], 'FATTYACID'] = 0
```

```
totals.loc[(totals['FARATIO'] > totals['FARMIN']) & (totals['FARATIO'] < totals['FARMAX']), 'FATTYACID'] = 10 * ((totals['FARATIO'] - totals['FARMIN']) / (totals['FARMAX'] - totals['FARMIN']))

totals['SODDEN'] = totals[sodium] / totals[kcal]
totals['SODMIN'] = 1.1
totals['SODMAX'] = 2.0
totals.loc[totals['SODDEN'] <= totals['SODMIN'], 'SODIUM'] = 10
totals.loc[totals['SODDEN'] >= totals['SODMAX'], 'SODIUM'] = 0
totals.loc[(totals['SODDEN'] > totals['SODMIN']) & (totals['SODDEN'] < totals['SODMAX']), 'SODIUM'] = 10 - (10 * (totals['SODDEN'] - totals['SODMIN']) / (totals['SODMAX'] - totals['SODMIN']))

totals['RGDEN'] = totals[g_refined] / (totals[kcal] / 1000)
totals['REFINEDGRAIN'] = 10 - (10 * (totals['RGDEN'] - 1.8) / (4.3 - 1.8))
totals.loc[totals['RGDEN'] <= 1.8, 'REFINEDGRAIN'] = 10
totals.loc[totals['RGDEN'] >= 4.3, 'REFINEDGRAIN'] = 0

totals['SFAT_PERC'] = 100 * (totals[satfat] * 9 / totals[kcal])
totals['TOTSATFAT'] = 10 - (10 * (totals['SFAT_PERC'] - 8) / (16 - 8))
totals.loc[totals['SFAT_PERC'] >= 16, 'TOTSATFAT'] = 0
totals.loc[totals['SFAT_PERC'] <= 8, 'TOTSATFAT'] = 10

totals['ADDSUG_PERC'] = 100 * (totals[add_sugars] * 16 / totals[kcal])
totals['ADDSUG'] = 10 - (10 * (totals['ADDSUG_PERC'] - 6.5) / (26 - 6.5))
totals.loc[totals['ADDSUG_PERC'] >= 26, 'ADDSUG'] = 0
totals.loc[totals['ADDSUG_PERC'] <= 6.5, 'ADDSUG'] = 10

totals['TOTAL_SCORE'] = totals[['TOTALVEG', 'GREEN_AND_BEAN', 'TOTALFRUIT',
                           'WHOLEFRUIT', 'WHOLEGRAIN', 'TOTALDAIRY',
                           'TOTPROT', 'SEAPLANT_PROT', 'FATTYACID',
```

```
                        'SODIUM', 'REFINEDGRAIN', 'TOTSATFAT',
                        'ADDSUG']].sum(axis=1)
    return totals
label_dict = {
        'TOTAL_SCORE': 'TOTAL HEI-2015 SCORE',
        'TOTALVEG': 'HEI-2015 COMPONENT 1 TOTAL VEGETABLES',
        'GREEN_AND_BEAN': 'HEI-2015 COMPONENT 2 GREENS AND BEANS',
        'TOTALFRUIT': 'HEI-2015 COMPONENT 3 TOTAL FRUIT',
        'WHOLEFRUIT': 'HEI-2015 COMPONENT 4 WHOLE FRUIT',
        'WHOLEGRAIN': 'HEI-2015 COMPONENT 5 WHOLE GRAINS',
        'TOTALDAIRY': 'HEI-2015 COMPONENT 6 DAIRY',
        'TOTPROT': 'HEI-2015 COMPONENT 7 TOTAL PROTEIN FOODS',
        'SEAPLANT_PROT': 'HEI-2015 COMPONENT 8 SEAFOOD AND PLANT PROTEIN',
        'FATTYACID': 'HEI-2015 COMPONENT 9 FATTY ACID RATIO',
        'SODIUM': 'HEI-2015 COMPONENT 10 SODIUM',
        'REFINEDGRAIN': 'HEI-2015 COMPONENT 11 REFINED GRAINS',
        'TOTSATFAT': 'HEI-2015 COMPONENT 12 SAT FAT',
        'ADDSUG': 'HEI-2015 COMPONENT 13 ADDED SUGAR',
        'VEGDEN': 'DENSITY OF TOTAL VEGETABLES PER 1000 KCAL',
        'GRBNDEN': 'DENSITY OF DARK GREEN VEG AND BEANS PER 1000 KCAL',
        'FRTDEN': 'DENSITY OF TOTAL FRUIT PER 1000 KCAL',
        'WHFRDEN': 'DENSITY OF WHOLE FRUIT PER 1000 KCAL',
        'WGRNDEN': 'DENSITY OF WHOLE GRAIN PER 1000 KCAL',
        'DAIRYDEN': 'DENSITY OF DAIRY PER 1000 KCAL',
        'PROTDEN': 'DENSITY OF TOTAL PROTEIN PER 1000 KCAL',
        'SEAPLDEN': 'DENSITY OF SEAFOOD AND PLANT PROTEIN PER 1000 KCAL',
        'FARATIO': 'FATTY ACID RATIO',
        'SODDEN': 'DENSITY OF SODIUM PER 1000 KCAL',
        'RGDEN': 'DENSITY OF REFINED GRAINS PER 1000 KCAL',
```

```
        'SFAT_PERC': 'PERCENT OF CALORIES FROM SAT FAT',
        'ADDSUG_PERC': 'PERCENT OF CALORIES FROM ADDED SUGAR'
    }

totals.rename(columns=label_dict, inplace=True)

outdat = 'output_totals.csv'
totals.to_csv(outdat, index=False)

calculate_hei2015(indat='output_totals.csv', kcal='KCAL', vtotalleg='VTOTALLEG',
vdrkgrleg='VDRKGRLEG',
                f_total='F_TOTAL', fwholefrt='FWHOLEFRT', g_whole='G_WHOLE', d_total='D_TOTAL',
                pfallprotleg='PFALLPROTLEG', pfseaplantleg='PFSEAPLANTLEG', monopoly='MONOPOLY',
                satfat='SFAT', sodium='SODI', g_refined='G_REFINED', add_sugars='ADD_SUGARS',
                outdat='output_totals_hei2015.csv')

# Call the function
result_totals = calculate_hei2015(indat='output_totals.csv', kcal='KCAL', vtotalleg='VTOTALLEG',
vdrkgrleg='VDRKGRLEG',
                                f_total='F_TOTAL', fwholefrt='FWHOLEFRT', g_whole='G_WHOLE',
d_total='D_TOTAL',
                                pfallprotleg='PFALLPROTLEG', pfseaplantleg='PFSEAPLANTLEG',
monopoly='MONOPOLY',
                                satfat='SFAT', sodium='SODI', g_refined='G_REFINED', add_sugars='ADD_SUGARS',
                                outdat='output_totals_hei2015.csv')

# Print the 'TOTAL_SCORE' column
print(result_totals[['TOTALVEG', 'GREEN_AND_BEAN', 'TOTALFRUIT',
                   'WHOLEFRUIT', 'WHOLEGRAIN', 'TOTALDAIRY',
                    'TOTPROT', 'SEAPLANT_PROT', 'FATTYACID',
```

```
                'SODIUM', 'REFINEDGRAIN', 'TOTSATFAT',
                'ADDSUG', 'TOTAL_SCORE']])

result_totals[['TOTALVEG', 'GREEN_AND_BEAN', 'TOTALFRUIT',
               'WHOLEFRUIT', 'WHOLEGRAIN', 'TOTALDAIRY',
                'TOTPROT', 'SEAPLANT_PROT', 'FATTYACID',
                'SODIUM', 'REFINEDGRAIN', 'TOTSATFAT',
                'ADDSUG', 'TOTAL_SCORE']].to_csv('output.csv', index=False)
```

Appendix B

Dataset 1

UPC NUMBER	Product
888670081440	Wellsley Farms Peanut Butter Filled Pretzels, Peanut Butter
860052001253	100% Organic Cotton Day Pads with Wings, Regular, 500PK
860052001222	100% Organic Cotton Tampons Regular 500/Carton
41188032612	6 Cans of Furman's Italian-Style Spaghetti Sauce 15 oz Can
843369101953	BARNANA ORGANIC PLANTAIN CRISPS, SEA SALT, 5 OUNCE BAG (6 BAGS TOTAL)
854702007047	Premier Pantry Beef pasta
8697480063483	Besler Wheat Flour Big Pouch - 900G X 1 PCS
10016000165394	Betty Crocker Dunkaroos Vanilla Cookies & Vanilla Frosting, 12 Count (Pack of 3)
10041570057251	Blue Diamond Almonds Ls Light Salt 16 oz., PK6
850018463027	Bonne Maman 12 Days of Christmas Spread and Honey Gift Set
858023005287	California Seedless Raisins - Sun Valley - 15 oz
884912356345	Cereal Post Honey Bunches Of Oats / 2 Pack / 1.41 Kg
16000138964	Cheerios Cereal-in-a-Cup - Original - 1 Serving Cup - 1.30 oz
50041760091162	Cherry Central Cooperative Inc Unsweetened Apple Sauce Cups 96/4.5
10016000199436	Chex Mix Peanut Butter Chocolate Bar - King Size - 12 Count ...
722252568038	Clif Nut Butter Filled Peanut Butter Energy Bar, 1.76 Ounce -- 144 per case
19722155752	Crider White Chicken 12.5 oz (24 Pack)
70074641157	Ensure High Protein Nutritional Shake, 16G Protein, Milk Chocola
70074670867	Ensure Plus Liquid Nutrition Shake with Fiber, 16 Grams of Protein, , Vanilla, 8 Fl Oz Bottle (Pack of 24)
70074671123	Ensure Plus Nutrition Vanilla Shake 8 Oz (Pack of 30)
876063811996	Fast Twitch Energy Drink Variety Pack, 12 pk./12 oz.
28400577595	Frito-Lay Holiday Mix Variety Pack (50 ct.)
715001110602	Garbanzo Beans / Chickpeas by American Beauty 15 Ounce Cans (Pack of 5)
10052000043195	GATORADE ZERO GLCR CHERRY 8PK, 3, 20 OZ,
76850099082	GOSSNER FOODS 1% Lowfat Shelf Stable Milk, 1 Quart, 12 Count
81864000696	Hampton Farms Creamy Peanut Butter,4 PK,16 oz Jars,100% USA peanuts,From NC Farm
10013700431286	Hefty Everyday Foam Snack Plates, 7 Inch Round, 54 Count (Pack of 8)
834192004085	Instant Nonfat Dry Milk - Mountain maid - 12.8 oz
10010700702309	JOLLY RANCHER ORIGINAL HARD CANDY 7 OZ PEG BAG
78742370859	Kidney Beans Dark Red 15 oz -15.25 oz
21000049486	Kraft Real Mayo Creamy & Smooth Mayonnaise 2 ct pack 30 fl oz Jars
10034500631560	Land O Lakes Mini Moo's Half and Half Single Serve Cups 24-Pack - 6/Case
5023471002194	Lavazza Starbucks Blonde Espresso Freshpack - Compatible with Flavia - Espresso, Creamy - Blonde - 72 / Each
42396253325	LOT 6 Mother's Maid Light Red Kidney Beans, 15oz EA
893262001959	Market Street Classics Premium Beef Stew Pouches Ready to Serve 24 oz Each
10059290311416	MCVITIE'S DIGESTIVE WHEAT BISCUITS 14.1 OZ BOX
193968007072	Member's Mark European 4-Pack Tin Shortbread Cookies 56.4 oz

854702007009	Menu Flavor Cheeseburger - Premier Pantry - 5.8 oz
73934153432	Mission Pride Fruit Mix In Extra Light Syrup 15oz. Cans
10725342260710	Muir Glen Organic Diced Tomatoes, 14.5 Ounce -- 12 per case
725342260713	Muir Glen Organic Diced Tomatoes, 14.5 oz.
16000104136	Nature Valley Sweet & Salty Almond Granola Bars (1.2 oz. bars, 36 ct.)
31200001085	Ocean Spray Juice Beverage Variety Pack, 18 Count
70074687865	PEDIASURE GROW & GAIN WITH FIBER, 3G FIBER 7.4 FL OZ (PACK OF 24)
14100074809	Pepperidge Farm Herb Seasoned Classic Stuffing 16 oz. Bags 3-Pack Box
73030156009	Pink Salmon Deep Sea Wild Alaska Canned 14.75 Oz Can
884912014283	Post Honey Bunches of Oats with Almonds, 48 oz.
854702007108	Premier Pantry Macaroni and "Real Cheese" Dinner, Mac N Cheese 7.25 oz
10840224600054	Primal Kitchen - Gravy Turkey Bn/brth - Case Of 6-12 Oz
70619211440278	Regal 1 lb. Spaghetti Pasta - 20/Case
813314010579	Saccharin Pink Sweetener, 2000 count per pack.
70074562674	Similac Special Care 24 With Iron And Mixed Carotenoids
10070462008231	Sour Patch Kids Bag, 12 Ounces, 12 per case, Price/case
854702007016	Premier Pantry Stroganoff
28400499323	SunChips® Variety Mix, Assorted Flavors, 1.5 oz Bags, 30 Bags/Box
10016000158938	SWT N SALTY MINI GRAN BAR PNT 20CT5/15 OZ
10021000047205	Taco Bell Mild Taco Sauce, 7.5 Ounce -- 12 per case.
10046000288755	TACO SEASONING MX HOT N SPICY32/1 OZ, 1 OZ
638102687517	ZONE DK CHO ALMD 45G BAR 2-10PKS
638102677785	ZONE DK CHO ALMD 45G BAR 4-5PKS
638102667496	ZonePerfect Protein Bars, 12g Protein, 18 Vitamins & Minerals, Nutritious Snack Bar, Double Dark Chocolate, 20 Bars
638102677846	Zoneperfect Strawberry Yogurt Bar, 1.76 Ounce, 5 Per Box -- 4 Per Case
	Potatoes, white
	Corn, whole cob
	Cantaloupe, whole melon
	Tomatoes, beefsteak
	Potatoes, sweet
	Carrots, whole
	bell peppers, mixed
	cabbage, whole
	Plums
	Mangos
	Grapes, white, bagged
	Pears, Bartlett
	butternut squash
	Apples
	Onions
	Zucchini
	Peaches
	Pineapples

	Bananas

Dataset 2

Name	UPC	QTY Received (cases)	Units/case	weight
Garbanzo Beans	71500111060	1530	24	15oz
White potatoes	n/a	840	5	10lb
FZ Shrimp	748631307302	1500	10	2lb
Milk, 2%	815473010339	1080	4	1gal
Eggs, medium	0088742200000	875	15	1 dozen
Collard greens	n/a	490	1	26lb
Sweet potatoes	n/a	500	1	40lb
Mandarins	n/a	1200	6	5lb
FZ chicken, whole	n/a	47	1	60lbs
Pineapple	n/a	1440	1	27lb
Onion	n/a	520	16	3lb
Cantaloupe	n/a	570	1	32lb
Honeydew	n/a	756	1	28lb
White potatoes	n/a	840	5	10lb
Zucchini	n/a	630	1	20lb
Bell Peppers	n/a	504	1	25lb
Cabbage	n/a	280	1	45lb
Chilli w. beans	893262001973	3264	12	15oz
FZ Fish Sticks	10028029189442	475	20	4lb
FZ Pork Chops	unknown	950	10	1lb
Grapefruit	n/a	940	1	36.5lb
Oranges	n/a	1026	1	36.5lb
Apples	n/a	924	1	38.5lb
Apples	n/a	980	12	3lb
Milk, Aseptic	unknown	1615	12	32oz
cornflakes	70038595489	1344	12	18oz
vegetable oil	876941003383	2240	24	12oz
Juice, Apple	unknown	1492	12	33.8oz
Clementines	n/a	165	10	3lb
caluflower, rainbow	n/a	130	1	25lb