Declarative Nutritional Knowledge Scores and Their Effect on Accurate Macro Nutrient Evaluation in Foods Consumed on Binghamton University's Campus

Anna Vishnevetsky

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Obesity has long been a problem in the United States, with obesity rates increasing exponentially over the last twenty years. A factor contributing to the rising obesity rate can be attributed to a lack of consumer nutritional knowledge. Specifically, because if consumers are unaware of the adverse health effects of the foods they consume, they are more likely to consume an excess of unhealthy and fattening foods. This problem is especially prevalent among college students, as they are just entering adulthood and forming lifelong dietary habits. This study aims to examine the relationship between college students' declarative nutritional knowledge and their practical knowledge of the dietary quality of food items in the university dining hall. The question this study aims to answer is whether there is an association between declarative nutritional knowledge and nutrition accuracy scores for dining hall foods consumed daily by students. Data were collected from a convenience sample through campus tabling, flyer distribution, and in-class recruitment. This data was then cleaned and analyzed in R using a Pearson correlation test to determine statistical significance. As in some of the inconsistent results reported in studies discussed throughout this paper, the test showed no statistically significant relationship between declarative nutritional knowledge and nutritional accuracy scores. However, it would be difficult to generalize the results of this study due to the limited sample size and location (a small sample of Binghamton University students). This topic could, if studies continue, potentially demonstrate the positive effect of nutritional knowledge on college students' awareness of the dietary quality of the foods they eat daily.

Table of contents

1 Introduction

1.1 Significance

Obesity has become one of the most pressing problems facing the public health of the United States over the last two decades, linked with prevalent chronic diseases such as hypertension, heart disease, and diabetes. Commonly cited individual risk factors for obesity include a lack of physical activity and unhealthy eating habits (Alotaibi et al., 2023). Despite the prevalence of these individual risk factors for adulthood obesity, a socioecological framework reveals additional risk factors that affect individuals' eating behaviors and, consequently, their health outcomes. One of these risk factors is an individual's nutritional knowledge that informs their decision-making. According to Alotaibi et al., a crucial step in addressing obesity and poor dietary habits is to ensure that proper macronutrient labels are placed on all food items available to consumers, enabling them to make informed dietary choices (Alotaibi et al., 2023). Furthermore, a study associating college students' level of nutritional knowledge with their daily fat consumption found that nutritional knowledge is negatively correlated with daily fat and cholesterol intake among college students (Yahia et al., 2016).

Within a socioecological framework of intervention, multiple policies can be enacted by legislative bodies to improve nutrition literacy. For instance, providing nutrition and calorie information on all restaurant and fast food menus. A similar policy was implemented in Saudi Arabia in 2019, aiming to promote informed decision-making and reduce obesity rates within the country (Alotaibi et al., 2023). Policies such as these are critical to young adult populations, especially college students, as they are forming routines and habits that will likely persist into adulthood. According to the Academy of Nutrition and Dietetics, dietary choices during early adulthood can significantly impact one's risk of obesity in later adulthood, thereby affecting their risk for numerous negative health outcomes associated with the disease (Zigmont & Bulmer, 2015). It is not only college students who are at increased risk of obesity; obesity risk is also highly affected by a number of demographic factors such as socioeconomic status, gender, age, lack of social support, and even genetics (Alotaibi et al., 2023). Despite there being particular groups that may be more at risk for the development of obesity, it is still a universal problem; in fact, obesity affects over 40% of Americans, and these figures will likely continue to rise without proper legislative intervention nationwide (Emmerich et al., 2024). Additionally, estimates show that treating obesity related illness accounts for more than 10% of the nation's medical spending (147 billion). In 2006, it was estimated that obese individuals spend an average of $1500 more on medical expenses annually than people of a normal weight (Mixon & Davis, 2020). Obesity is a disease affecting tens of millions of Americans and will likely only continue to grow more prevalent. However, the presentation of new evidence showing that the provision of nutritional information and increased nutritional knowledge may be linked to consumers engaging in healthier eating behaviors lends hope for the development of more effective obesity interventions in the near future (Zigmont & Bulmer, 2015).

1.2 Knows and Unknowns

A common form of nutritional information for consumers is the Nutrition Facts Panel (NFP) , which is found on all packaged foods in the US. These are the most utilized sources of nutritional knowledge for consumers. NFPs include calories, as well as a food's macro and micronutrients, including fat, sugar, cholesterol, and sodium. (Mixon & Davis, 2020). Additionally, in nutritional knowledge assessment questionnaires, there are two defined definitions of nutritional knowledge: declarative knowledge and procedural knowledge. Declarative nutritional knowledge is factual nutritional knowledge, such as the statement "oily fish contains polyunsaturated fatty acids." Procedural nutritional knowledge, which is thought to be more predictive of better eating habits, is knowing how to compose and prepare a healthy meal (Dickson-Spillmann et al., 2011). According to the World Health Organization (WHO) obesity in adults is defined as a Body Mass Index (BMI) greater than or equal to 30. In the case of nutritional interventions, characterized by efforts to increase nutritional knowledge among consumers, a socioecological perspective provides a more effective framework, as several factors can affect the efficacy of such interventions. On the individual level, these interventions could be affected by an individual's accurate knowledge of the nutritional content of the foods they consume. Institutional factors could include the food available for consumption in a specific location, such as a university with dining halls. Legislative factors would include policies on food labeling, specifically the implementation of NPFs or calorie labeling in restaurants (Zigmont & Bulmer, 2015).

There are a few meta-analyses of the effects of nutritional knowledge on eating behaviors. One example is a meta-analysis conducted on the effects of nutrition labels on dietary quality in college students. This analysis examined 22 different studies and identified that 16 of these studies found nutrition label exposure to be associated with improved diet (Christoph & An, 2018). Additionally, a randomized control trial (RCT) in Malaysia examining the relationship between nutritional knowledge interventions and dietary intake found that subjects in the intervention group significantly improved the nutritional quality of their diet within the ten-week experiment, compared with those in the control group (Shahril et al., 2013). Despite the numerous studies, there are still areas that researchers have yet to explore, and some contradictory evidence remains. For example, while several studies have reported that nutrition education may improve students' dietary habits, other studies have found no significant correlation between nutritional knowledge and one's food choices (Yahia et al., 2016). Additionally, it is clear that nutrition knowledge is not the only determinant of dietary behaviors, and that there is an extensive range of other influences, including the time of day, the sensory appeal of a food, and even cultural and demographic factors (Dickson-Spillmann et al., 2011). Thus, while it is known that nutritional knowledge level, be it procedural or declarative, may have some effect on the dietary choices of an individual, it is difficult to judge the scope of this effect because of the confounding variables that may affect dietary intake, which are very difficult to control for in studies examining this relationship.

1.3 Research Aims

There are a number of gaps in nutrition knowledge and intervention research. One gap that exists is a general lack of understanding of college students' thought processes while making food choices. While these choices may be influenced by their nutritional knowledge, many other factors may also contribute to their choices (Zigmont & Bulmer, 2015). Another large methodological gap is the lack of dietary outcomes assessed. Most reviews have focused exclusively on collecting data on calorie intake, even though the scope of dietary intake should be a much broader measure. There are only a very small number of studies that have used an expanded definition of dietary intake. Thus, this data is not easily comparable with the larger pool of studies that focus exclusively on calorie intake as the sole measure of dietary intake. This study employs an exploratory approach to assess a broader definition of dietary quality, encompassing both macronutrients and calories. The purpose of this study is to examine the relationship between college students' declarative nutritional knowledge and their practical knowledge concerning the dietary quality (calories and macronutrients) of the food items within the university dining hall. The question this study aims to answer is whether there is an association between declarative nutritional knowledge and nutrition accuracy scores of dining hall foods consumed daily by students. The predicted results of this study are that there will be a positive association between students' declarative nutritional knowledge and their nutritional accuracy scores.

2 Methods

2.1 Participants and Sampling

The study was approved by the Institutional Review Board of a public higher education institution in New York. Research was conducted ethically to protect the rights, welfare, confidentiality, and privacy of participants. Also, participants were informed of the project and provided their consent before beginning the survey. Participants were eligible to participate in the study if they were at least 18 years of age, attended Binghamton University as an undergraduate student, and had a resident campus meal plan. A convenient sample was recruited by campus tabling, distributing flyers, and in-class recruitment. The sample size for this study was 209 Binghamton University students. Data was collected via survey using Qualtrics; two sections from within the larger Qualtrics survey were included in the analysis for this study, from sections "Nutrition Knowledge Quiz" and "Macro Accuracy," including eight and five items, respectively.

2.2 Measures

For the purpose of this study, nutritional knowledge is defined as a declarative nutritional knowledge score, ranging from 0 to 8, with 8 being the highest score and 0 being the lowest score. Macronutrient accuracy refers to the student's ability to accurately determine the calories, saturated fat, carbohydrates, sugar, and protein of food items within the university dining hall. Items were created for the macronutrient accuracy using a ratio scale, referencing the Sodexo MyWay website, which shares the NFPs for all foods made in the Binghamton University dining halls. The measure consists of 5 items: 1) Select the number of calories in each food item from the dining hall, 2) select the amount of saturated fat (in grams) in each food item from the dining hall, 3) select the amount of carbohydrates (in grams) in each food item from the dining hall, 4) select the amount of sugar (in grams) in each food item from the dining hall, 5) Select the amount of protein (in grams) in each food item from the dining hall. The items were scored using a slider tile that ranged from a low to a high numeric value. Declarative nutritional knowledge scores were measured using the nutrition knowledge scale (Dickson-Spillmann et al., 2011) with the response of options of T (true) or F (false). Accuracy scores from each item for macronutrient accuracy were combined to create a composite score (accuracy scores were calculated for each item by subtracting the reported value from the actual value; these item scores were then combined to produce a composite score). Each item for declarative nutritional knowledge was combined to create a composite score (the scores for each item were summed to create a composite score).

2.3 Data Analysis Plan

Data was exported from Qualtrics in a numerical format and imported into Posit Cloud. R code provided in "The Quantitative Playbook for Public Health Research in R" (McCarty, 2025) was modified to install R packages (see 'install.R') and import data using'readr (`10.20.2025.perceptionsdata.team5.clean.xlsx`). Values were then created representing each of the true macronutrient counts for each item of the macronutrient accuracy assessment (`CAL_true`, `FAT_true`, `CARB_true`, `SUG_true`, `PRO_true`). The R package `dplyr` was then used to calculate accuracy scores by subtracting the reported scores from the true scores (using absolute value to guarantee no negative scores). These difference scores were then summed across each item to create multiple composite accuracy scores (`SUM_CAL_abs_diff`, `SUM_FAT_abs_diff`, `SUM_CARB_abs_diff`, `SUM_SUG_abs_diff`, `SUM_PRO_abs_diff`). These composite scores were then summed into a single score to determine the overall macronutrient score (`TOTAL_abs_diff`). Similarly, nutritional knowledge scores (KNOW_total) were created by summing scores for each item (`KNOW_1`, `KNOW_2`, `KNOW_3`, `KNOW_4`, `KNOW_5`, `KNOW_6`, `KNOW_7`, `KNOW_8`).

A descriptive statistics table was then constructed using inline R code, displaying summary statistics for nutritional knowledge and macronutrient accuracy scores (`KNOW_total`, `TOTAL_abs_diff`). Histograms were then visualized using the R package `ggplot2` to ensure normality of the two variables. This study aimed to analyze the relationship between participants' nutritional knowledge scores and their practical macronutrient assessment accuracy. Thus, a Pearson correlation was run to determine the relationship between the two variables (`TOTAL_abs_diff`, `KNOW_total`). This relationship was then modeled on a scatter plot using the R package `ggplot2`.

2.4 Load

```
library(tidyverse)
library(psych)
library(knitr)
library(tibble)
library(dplyr)
library(tidyr)
library(ggplot2)
library(hexbin)
library(scales)     # for number formatting like comma()
library(english)    # to convert numbers to words
library(stringr)    # for text functions like str_c()
library(NHANES)
library(haven)
library(readxl)
# source: (Hei & McCarty, 2025) https://shanemccarty.github.io/FRIplaybook/import-once.html
```

```
library(readxl)
```

2.5 Import

```
library(readxl)
library(dplyr)
primary_data <- read_excel("/cloud/project/10.20.2025.perceptiondata.team5.clean.xlsx", col_nar
# source:  (Hei & McCarty, 2025) https://shanemccarty.github.io/FRIplaybook/import-once.html
# explanation: import perceptions survey data as data frame primary_data
```

2.6 Transform

2.6.1 Filter out NAs

```
primary_data[primary_data == -99] <- NA
# source: (Hei & McCarty, 2025) https://shanemccarty.github.io/FRIplaybook/import-once.html
# explanation: Filtered out NA responses from primary_data and used names() and summary() funct
```

2.6.2 Defining True Values

```r
## list of calories for each food
CAL_true <- c(
  BACON_CAL_true = 250,  # true value for food 1
  EGGS_CAL_true = 180,  # true value for food 2
  TOTS_CAL_true = 320,  # true value for food 3
  SESRICE_CAL_true = 150,  # true value for food 4
  SESCHICK_CAL_true = 140, # true value for food 5
  SPROUTS_CAL_true = 150, #true value for food 6
  KORCHICK_CAL_true = 300, #true value for food 7
  BOK_CAL_true = 60, #true value for food 8
  VEGGIERICE_CAL_true = 150  #true value for food 9
)
## list of fat for each food
FAT_true <- c(
  BACON_FAT_true = 1.5,  # true value for food 1
  EGGS_FAT_true = 4.5,  # true value for food 2
  TOTS_FAT_true = 3,  # true value for food 3
  SESRICE_FAT_true = 0, # true value for food 4
  SESCHICK_FAT_true = 1, # true value for food 5
  SPROUTS_FAT_true = 1, # true value for food 6
  KORCHICK_FAT_true = 4.5, # true value for food 7
  BOK_FAT_true = 0.5, # true value for food 8
  VEGGIERICE_FAT_true = 0 # true value for food 9
)
## list of carbohydrates for each food
CARB_true <- c(
  BACON_CARB_true = 0,  # true value for food 1
  EGGS_CARB_true = 1,  # true value for food 2
  TOTS_CARB_true = 20,  # true value for food 3
  SESRICE_CARB_true = 21,  # true value for food 4
  SESCHICK_CARB_true = 0, # true value for food 5
  SPROUTS_CARB_true = 12, # true value for food 6
  KORCHICK_CARB_true = 7, # true value for food 7
  BOK_CARB_true = 3, # true value for food 8
  VEGGIERICE_CARB_true = 25 # true value for food 9
)
## list of sugar for each food
SUG_true <- c(
  BACON_SUG_true = 0,  # true value for food 1
  EGGS_SUG_true = 0,  # true value for food 2
  TOTS_SUG_true = 1,  # true value for food 3
  SESRICE_SUG_true = 0,  # true value for food 4
  SESCHICK_SUG_true = 0, # true value for food 5
  SPROUTS_SUG_true = 5, # true value for food 6
  KORCHICK_SUG_true = 4, # true value for food 7
  BOK_SUG_true = 1, # true value for food 8
  VEGGIERICE_SUG_true = 2 # true value for food 9
```

```
)
## list of protein for each food
PRO_true <- c(
  BACON_PRO_true = 5,  # true value for food 1
  EGGS_PRO_true = 13,  # true value for food 2
  TOTS_PRO_true = 2,  # true value for food 3
  SESRICE_PRO_true = 2,  # true value for food 4
  SESCHICK_PRO_true = 26, # true value for food 5
  SPROUTS_PRO_true = 2, # true value for food 6
  KORCHICK_PRO_true = 21, # true value for food 7
  BOK_PRO_true = 2, # true value for food 8
  VEGGIERICE_PRO_true = 4 # true value for food 9
)
# source: datacamp
# explain: created true values for every column of the macro-nutrient accuracy assessment. thes
```

2.6.3 Create Difference Scores

```
# Create absolute difference scores (absolute value of raw differences)
## combined absolute difference scores
primary_data <- primary_data %>%
  mutate(
## calorie absolute difference scores
  BACON_CAL_abs_diff = abs(CALORIES_1 - CAL_true["BACON_CAL_true"]),
  EGGS_CAL_abs_diff = abs(CALORIES_2 - CAL_true["EGGS_CAL_true"]),
  TOTS_CAL_abs_diff = abs(CALORIES_3 - CAL_true["TOTS_CAL_true"]),
  SESRICE_CAL_abs_diff = abs(CALORIES_4 - CAL_true["SESRICE_CAL_true"]),
  SESCHICK_CAL_abs_diff = abs(CALORIES_5 - CAL_true["SESCHICK_CAL_true"]),
  SPROUTS_CAL_abs_diff = abs(CALORIES_6 - CAL_true["SPROUTS_CAL_true"]),
  KORCHICK_CAL_abs_diff = abs(CALORIES_7 - CAL_true["KORCHICK_CAL_true"]),
  BOK_CAL_abs_diff = abs(CALORIES_8 - CAL_true["BOK_CAL_true"]),
  VEGGIERICE_CAL_abs_diff = abs(CALORIES_9 - CAL_true["VEGGIERICE_CAL_true"]),
  ## fat absolute difference scores
  BACON_FAT_abs_diff = abs(SATFAT_1 - FAT_true["BACON_FAT_true"]),
  EGGS_FAT_abs_diff = abs(SATFAT_2 - FAT_true["EGGS_FAT_true"]),
  TOTS_FAT_abs_diff = abs(SATFAT_3 - FAT_true["TOTS_FAT_true"]),
  SESRICE_FAT_abs_diff = abs(SATFAT_4 - FAT_true["SESRICE_FAT_true"]),
  SESCHICK_FAT_abs_diff = abs(SATFAT_5 - FAT_true["SESCHICK_FAT_true"]),
  SPROUTS_FAT_abs_diff = abs(SATFAT_6 - FAT_true["SPROUTS_FAT_true"]),
  KORCHICK_FAT_abs_diff = abs(SATFAT_7 - FAT_true["KORCHICK_FAT_true"]),
  BOK_FAT_abs_diff = abs(SATFAT_8 - FAT_true["BOK_FAT_true"]),
  VEGGIERICE_FAT_abs_diff = abs(SATFAT_9 - FAT_true["VEGGIERICE_FAT_true"]),
  ## carbohydrate absolute difference scores
  BACON_CARB_abs_diff = abs(CARBS_1 - CARB_true["BACON_CARB_true"]),
  EGGS_CARB_abs_diff = abs(CARBS_2 - CARB_true["EGGS_CARB_true"]),
```

```
  TOTS_CARB_abs_diff = abs(CARBS_3 - CARB_true["TOTS_CARB_true"]),
  SESRICE_CARB_abs_diff = abs(CARBS_4 - CARB_true["SESRICE_CARB_true"]),
  SESCHICK_CARB_abs_diff = abs(CARBS_5 - CARB_true["SESCHICK_CARB_true"]),
  SPROUTS_CARB_abs_diff = abs(CARBS_6 - CARB_true["SPROUTS_CARB_true"]),
  KORCHICK_CARB_abs_diff = abs(CARBS_7 - CARB_true["KORCHICK_CARB_true"]),
  BOK_CARB_abs_diff = abs(CARBS_8 - CARB_true["BOK_CARB_true"]),
  VEGGIERICE_CARB_abs_diff = abs(CARBS_9 - CARB_true["VEGGIERICE_CARB_true"]),
  ## sugar absolute difference scores
  BACON_SUG_abs_diff = abs(SUGAR_1 - SUG_true["BACON_SUG_true"]),
  EGGS_SUG_abs_diff = abs(SUGAR_2 - SUG_true["EGGS_SUG_true"]),
  TOTS_SUG_abs_diff = abs(SUGAR_3 - SUG_true["TOTS_SUG_true"]),
  SESRICE_SUG_abs_diff = abs(SUGAR_4 - SUG_true["SESRICE_SUG_true"]),
  SESCHICK_SUG_abs_diff = abs(SUGAR_5 - SUG_true["SESCHICK_SUG_true"]),
  SPROUTS_SUG_abs_diff = abs(SUGAR_6 - SUG_true["SPROUTS_SUG_true"]),
  KORCHICK_SUG_abs_diff = abs(SUGAR_7 - SUG_true["KORCHICK_SUG_true"]),
  BOK_SUG_abs_diff = abs(SUGAR_8 - SUG_true["BOK_SUG_true"]),
  VEGGIERICE_SUG_abs_diff = abs(SUGAR_9 - SUG_true["VEGGIERICE_SUG_true"]),
  ## protein absolute difference scores
  BACON_PRO_abs_diff = abs(PROTEIN_1 - PRO_true["BACON_PRO_true"]),
  EGGS_PRO_abs_diff = abs(PROTEIN_2 - PRO_true["EGGS_PRO_true"]),
  TOTS_PRO_abs_diff = abs(PROTEIN_3 - PRO_true["TOTS_PRO_true"]),
  SESRICE_PRO_abs_diff = abs(PROTEIN_4 - PRO_true["SESRICE_PRO_true"]),
  SESCHICK_PRO_abs_diff = abs(PROTEIN_5 - PRO_true["SESCHICK_PRO_true"]),
  SPROUTS_PRO_abs_diff = abs(PROTEIN_6 - PRO_true["SPROUTS_PRO_true"]),
  KORCHICK_PRO_abs_diff = abs(PROTEIN_7 - PRO_true["KORCHICK_PRO_true"]),
  BOK_PRO_abs_diff = abs(PROTEIN_8 - PRO_true["BOK_PRO_true"]),
  VEGGIERICE_PRO_abs_diff = abs(PROTEIN_9 - PRO_true["VEGGIERICE_PRO_true"])
  )
# source: (2024) https://www.projectpro.io/recipes/subtract-2-numbers-r
# explanation: created difference scores for true values (as defined in the previous code chun
```

2.6.4 Create Summed Difference Scores

```
library(dplyr)
# Create summed absolute difference scores
primary_data <- primary_data %>%
  mutate(
## sum calorie absolute difference scores
   SUM_CAL_abs_diff = BACON_CAL_abs_diff + EGGS_CAL_abs_diff + TOTS_CAL_abs_diff + SESRICE_CAL_
## sum fat absolute difference scores
    SUM_FAT_abs_diff = BACON_FAT_abs_diff + EGGS_FAT_abs_diff + TOTS_FAT_abs_diff + SESRICE_FA
## sum carbohydrate absolute difference scores
    SUM_CARB_abs_diff = BACON_CARB_abs_diff + EGGS_CARB_abs_diff + TOTS_CARB_abs_diff + SESRIC
## sum sugar absolute difference scores
    SUM_SUG_abs_diff = BACON_SUG_abs_diff + EGGS_SUG_abs_diff + TOTS_SUG_abs_diff + SESRICE_SU
```

```
## sum protein absolute differences
    SUM_PRO_abs_diff = BACON_PRO_abs_diff + EGGS_PRO_abs_diff + TOTS_PRO_abs_diff + SESRICE_PRO
  )
# source: https://rstudio.github.io/cheatsheets/html/data-transformation.html
# explanation: used mutate() function to create new columns that summed all the individual food
```

2.6.5 Create combined total difference scores

```
## create total absolute differences scores by summing all nutrient difference scores
primary_data <- primary_data %>%
  mutate(
    TOTAL_abs_diff = rowSums(across(c(
      SUM_CAL_abs_diff,
      SUM_FAT_abs_diff,
      SUM_CARB_abs_diff,
      SUM_SUG_abs_diff,
      SUM_PRO_abs_diff
    )))
  )
# source: https://dplyr.tidyverse.org/articles/rowwise.html
# explanation: took the sum of all the individual macro-nutrient difference score to obtain the
```

2.6.6 Create Knowledge Scores

```
library(dplyr)
#| label: total knowledge score
## create 'KNOW_total' which is the sum of all KNOW columns
primary_data <- primary_data %>%
  mutate(
    KNOW_total = KNOW1 + KNOW2 + KNOW3 + KNOW4 + KNOW5 + KNOW6 + KNOW7 + KNOW8
  )
# source: https://rstudio.github.io/cheatsheets/html/data-transformation.html
# explanation: created total nutritional knowledge score by summing the 'know' columns, which c
```

3 Results

3.1 Demographics

The study sample consisted entirely of Binghamton University students (N = 208), and participants were between the ages of 18 and 22, with a mean age of 18.94 years. Female students accounted for about 70% of the sample, and about 80% of participants were White or Asian. According to the Binghamton University statistics, about 51% of students are female, and about 66% of students identify as either White or Asian (Binghamton University | Data USA, n.d.). Thus, this sample may be somewhat unrepresentative of Binghamton University's demographics, as it includes significantly more female, White, and Asian students than the general Binghamton University population, which may make it difficult to generalize the study's results to the larger population.

Displayed in Table 1 are the means and standard deviations of both variables, total nutritional knowledge (M = 6.405, SD = 1.428, n= 79) and total macro nutrient accuracy scores (combined calories, saturated fat, carbohydrate, sugar, and protein) (M = 843.837, SD = 242.650, n = 79). Total macronutrient accuracy score was calculated as the sum of the differences between individual macronutrient accuracy scores.

Variable	n	Mean	Median	SD	Min	Max
`KNOWLEDGE SCORE`	79	6.41	7	1.43	0	8
`ACCURACY SCORE`	43	843.84	821	242.65	466	1484

3.2 Primary Variables

Displayed in Figure 1 is a histogram of the distribution of participants' nutritional knowledge scores. The distribution appears to be left-skewed and is not a normal distribution. Displayed in Figure 2 is a histogram of the distribution of participants' macronutrient accuracy scores. The distribution appears to be right-skewed and is not a normal distribution. In order to run a Pearson Correlation test both variables tested must be normally distributed and sample size should be at least 30. Due to the sample size for this study being greater than 30 and the appearance of a normal distribution of residuals for both variables (as shown in Figure 3) it was deemed appropriate to conduct a Pearson Correlation test for association.

```
library(ggplot2)
## create a histogram to check for normality of 'KNOW_total`
ggplot(primary_data, aes(x = KNOW_total)) +
  geom_histogram(binwidth = .5) + theme_bw() + ggtitle("Participants' Knowledge Scores") + xlab
```

```
Warning: Removed 109 rows containing non-finite outside the scale range
(`stat_bin()`).
```

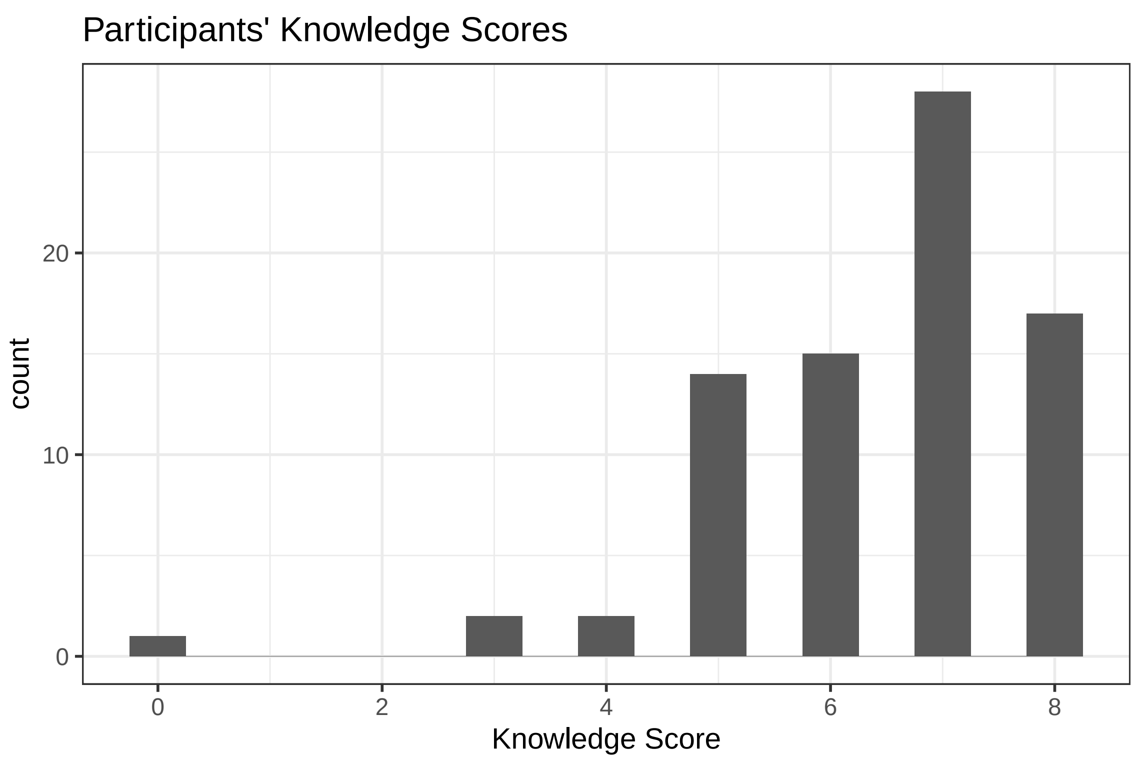


Figure 1: Figure 1. A histogram depicting the distribution of nutritional knowledge scores

```
ggsave("plot/knowledge_scores_hist.png" , width = 8, height = 6)
```

```
Warning: Removed 109 rows containing non-finite outside the scale range
(`stat_bin()`).
```

```
# source: https://rstudio.github.io/cheatsheets/data-visualization.pdf
# explanation: made a histogram to check for normal distribution of 'KNOW_total'.
```

```
library(ggplot2)
## create histogram to check for normality of 'TOTAL_abs_diff'
ggplot(primary_data, aes(x = TOTAL_abs_diff)) +
  geom_histogram(binwidth = 10) + ggtitle("Participants' Accuracy Scores") + xlab("Accuracy Sco
```

```
Warning: Removed 145 rows containing non-finite outside the scale range
(`stat_bin()`).
```

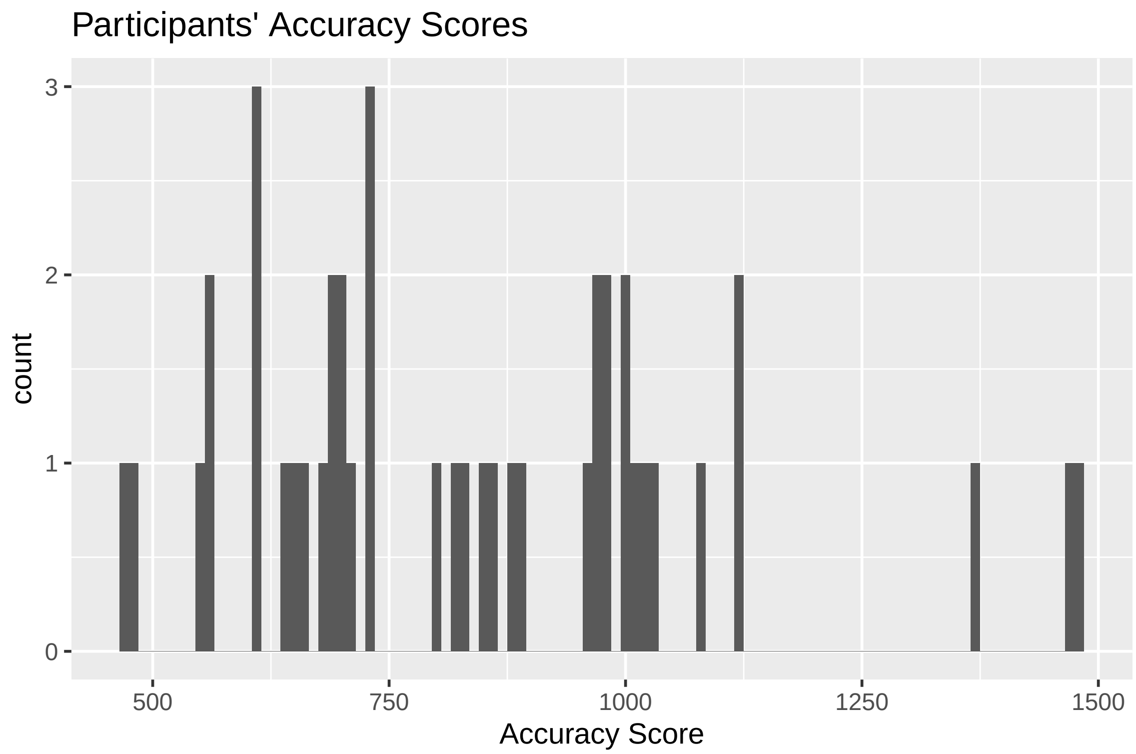


Figure 2: Figure 2. A histogram depicting the distribution of macro-nurtient accuracy scores.

```
ggsave("plot/accuracy_scores_hist.png" , width = 8, height = 6)
```

```
Warning: Removed 145 rows containing non-finite outside the scale range
(`stat_bin()`).
```

```
# source: https://rstudio.github.io/cheatsheets/data-visualization.pdf
# explanation: made a histogram to check for normal distribution of 'TOTAL_abs_diff'.
```

3.3 Knowledge and Accuracy

A Pearson correlation showed no statistically significant correlation between declarative nutritional knowledge and macro-nutrient accuracy scores ($r = -0.18$, $p = .257$). This suggests that there is no relationship between declarative nutritional knowledge and practical macronutrient knowledge. As shown in Figure 1, there is no correlation between declarative nutritional knowledge and macronutrient accuracy scores. Thus, these findings fail to reject the null hypothesis that declarative nutritional knowledge and macronutrient accuracy scores are not related.

```
library(ggplot2)
## create scatter plot to plot data
plot.knowledge.accuracy <- ggplot(data = primary_data, aes(x = KNOW_total, y = TOTAL_abs_diff))
  geom_point() +
  geom_smooth(method = "lm") +
```

```
  theme_bw() +
  ggtitle("Nutritional Knowledge vs. Macronutrient Accuracy") +
  xlab("Knowledge Score") +
  ylab("Accuracy Score")
plot.knowledge.accuracy <- plot.knowledge.accuracy + scale_x_continuous(breaks = seq(4, 8, by =
print(plot.knowledge.accuracy)
```

```
`geom_smooth()` using formula = 'y ~ x'
```

```
Warning: Removed 145 rows containing non-finite outside the scale range
(`stat_smooth()`).
```

```
Warning: Removed 145 rows containing missing values or values outside the scale range
(`geom_point()`).
```

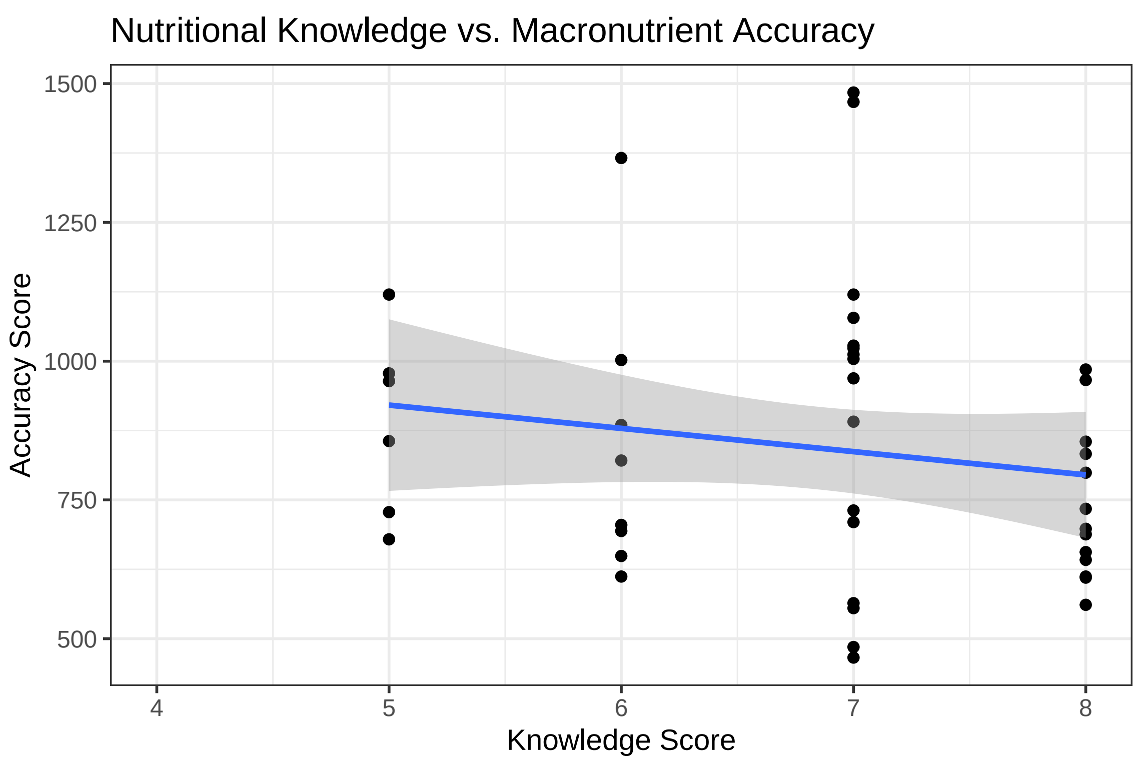


Figure 3: A scatterplot depicting the relationship between nutritional knowledge scores and macronutrient accuracy scores.

```
ggsave("plot/macro_knowledge_plot.png" , width = 8, height = 6)
```

```
`geom_smooth()` using formula = 'y ~ x'
```

```
Warning: Removed 145 rows containing non-finite outside the scale range
(`stat_smooth()`).
Removed 145 rows containing missing values or values outside the scale range
(`geom_point()`).
```

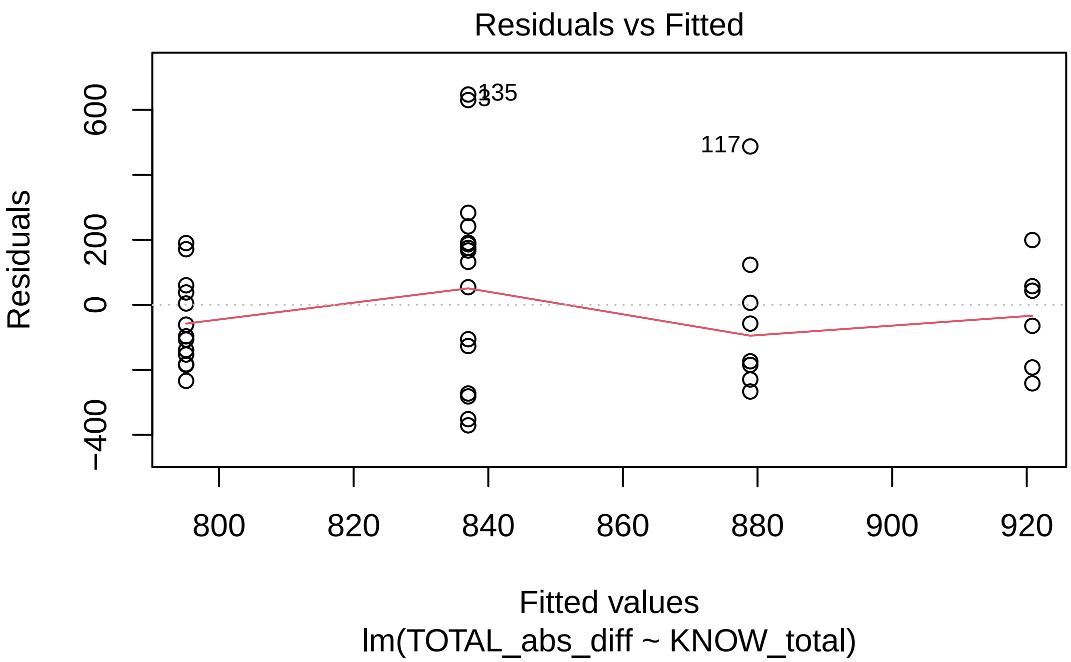
```
# source: https://rstudio.github.io/cheatsheets/html/data-visualization.html#two-variables---bo
# explanation: created scatter plot as a way to visualize the relationship between the two var
```

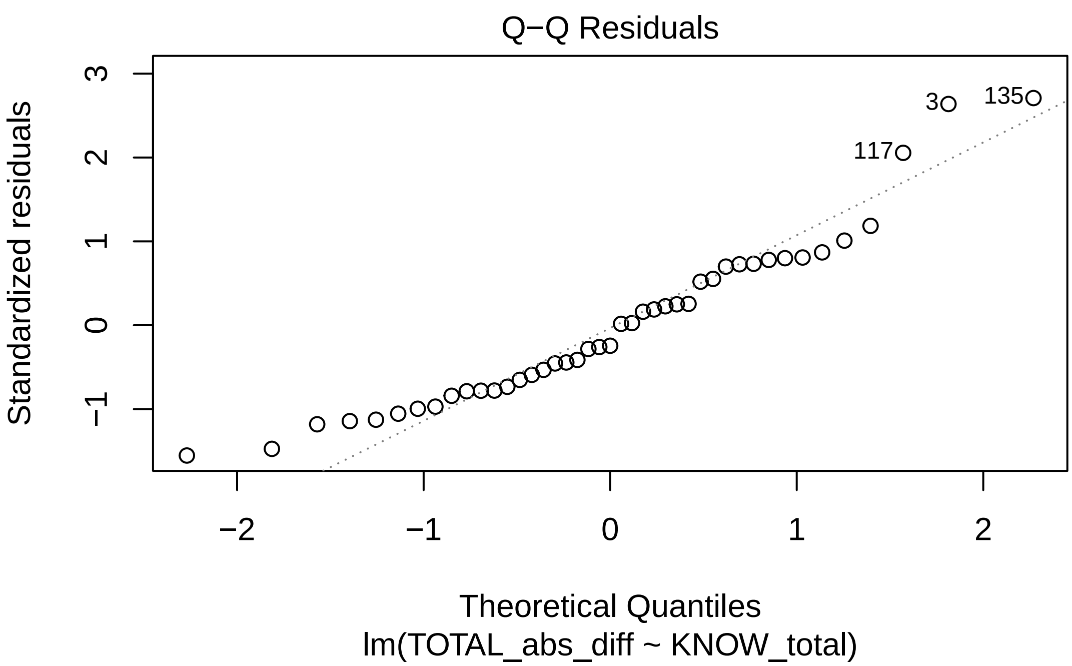
3.3.1 Fit to linear model to check for normality of residuals

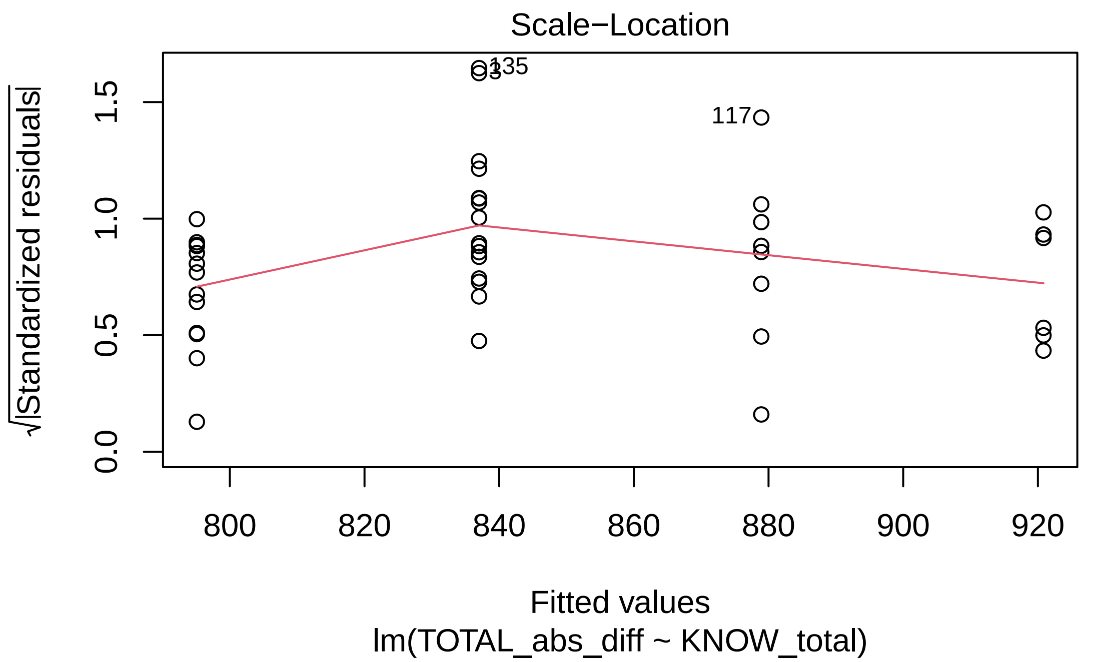
```
## check for normal distribution of residuals
### fit to linear model
lm_primary_data <- lm(TOTAL_abs_diff ~ KNOW_total , data = primary_data)
### summarize linear model
summary(lm_primary_data)
```

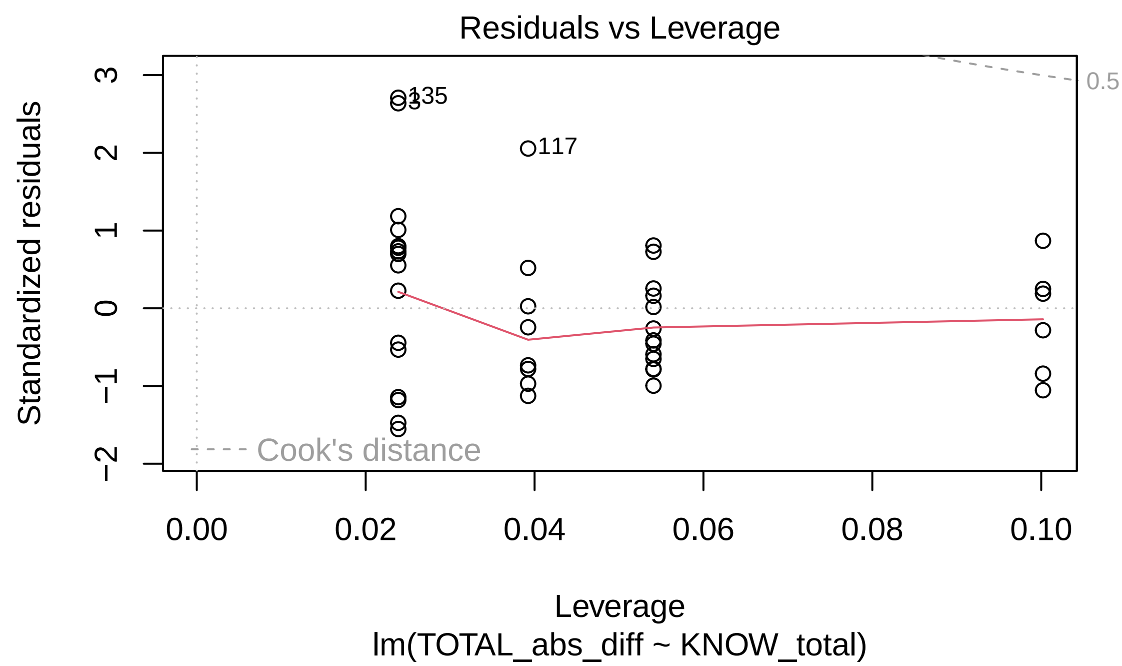
```
Call:
lm(formula = TOTAL_abs_diff ~ KNOW_total, data = primary_data)

Residuals:
    Min      1Q  Median      3Q     Max
-371.01 -184.01  -57.92  168.94  646.99

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1130.38     252.27   4.481 5.85e-05 ***
KNOW_total    -41.91      36.50  -1.148    0.258
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 241.7 on 41 degrees of freedom
  (145 observations deleted due to missingness)
Multiple R-squared:  0.03115,   Adjusted R-squared:  0.007521
F-statistic: 1.318 on 1 and 41 DF,  p-value: 0.2576
```

```
### plot linear model
plot(lm_primary_data)
```


Residuals vs Fitted
Residuals
Fitted values
lm(TOTAL_abs_diff ~ KNOW_total)
600
200
0
−400
800
820
840
860
880
900
920
135
3
117


Q−Q Residuals
Standardized residuals
Theoretical Quantiles
lm(TOTAL_abs_diff ~ KNOW_total)
3
2
1
0
−1
−2
135
117






```
## because residuals are normally distributed, run Pearson correlation test
# source: (2025) https://www.datacamp.com/tutorial/linear-regression-R
# explanation: fit both variables to a linear model in order to check for normal distribution o
```

3.3.2 Run Pearson correaltion

```r
## run pearson correlation

cor.test(primary_data$TOTAL_abs_diff, primary_data$KNOW_total, method = "pearson", use = "comp
```

```
	Pearson's product-moment correlation

data:  primary_data$TOTAL_abs_diff and primary_data$KNOW_total
t = -1.1482, df = 41, p-value = 0.2576
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4528362  0.1307794
sample estimates:
       cor 
-0.1764971 
```

4 Disucssion

The current study's findings suggest that declarative nutritional knowledge and practical nutritional accuracy scores for dining hall foods are not associated with one another. This study aimed to determine whether there was a link between Binghamton students' declarative (factual) nutritional knowledge and their ability to accurately assess the macronutrient content of dining hall foods they eat daily. The researchers expected to find that there was a positive relationship between declarative nutritional knowledge and macronutrient accuracy; however, after running a Pearson correlation, no statistically significant relationship was found between the two variables. This lack of significance may be attributable to the limited scope of the sample, which was a small sample (n=79) of Binghamton University students who were recruited through on-campus tabling. A number of confounding factors could be linked to this lack of relationship, for instance, the knowledge-behavior gap, which states that knowledge may not always be a good determinant of behavior (Kennedy et al., 2004). Additionally, a general lack of existing research on the relationship between declarative nutritional knowledge and the practical assessment of macronutrient content in food underscores the need for further research on this topic before a conclusion on the relationship between declarative and practical nutritional knowledge can be reached.

Even though this study did not find a significant relationship between declarative nutritional knowledge and macronutrient assessment accuracy, multiple studies have shown associations between various nutritional knowledge interventions and dietary quality, suggesting that declarative nutritional knowledge may be correlated with increased awareness of dietary quality (Shahril et al., 2013). However, these findings have been inconsistent, especially when researching college students (Yahia et al., 2016). Because of these inconsistent research results, future researchers may benefit from increasing research efforts on the effect of nutritional knowledge and food choices, as well as the link between declarative nutritional knowledge and its link to awareness of macro-nutrients in food consumed daily.

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