Life in the Fast Food Lane: Understanding the Factors Affecting Fast Food Consumption among Students in the Philippines

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The fast food industry in the Philippines is growing rapidly and is dominating the food service establishments. Together with this influx in fast food establishments is the increase in fast food consumption and an emergence of an unhealthy lifestyle and increase in obesity prevalence, not only among Filipinos, but around the world. The growth of the fast food industry has been aggressive, especially with its advertisements which have been known to target families and the youth. Previous studies have shown that the youth tend to be more affected by fast food obesity than adults. With this, the researchers decided to create a model for whether students eat at fast food chains using the 2011 Global school-based Student Health Survey in the Philippines. Before modelling, factor analysis was performed to bracket variables together. A total of 6 factors arose--namely vices, assistance from others, injuries and bullying, hygiene, active lifestyle, and diet. In modelling using the original variables, various methods were used for variable selection to reduce the forty-seven variables to a manageable number of predictors. These methods were the independent Chi-squared tests, Fisher Exact Tests, Forward and Backward Selection, and Analysis of Deviance. The resulting model showed that some of the most significant predictors for whether or not a student eats fast food is their frequency of drinking soft drinks, eating fruits, and feeling hungry due to lack of food in the house. The weight and sex of a student also significantly affected the response, in which the odds of eating at a fast food chain were for men were 33.84% lower than that of women, and a kilogram increase in a student's weight increased their odds by 2.5%.

Keywords: fast food, nutrition, factor analysis, logistic regression, Poisson loglinear model, negative binomial loglinear model, Global School-Based Student Health Survey

1. Introduction

In the Philippines, people all share a love for food. According to the 2015 Annual Survey of Philippine Business and Industry (ASPBI), a total of 27,028 establishments in one sector of the economy were linked to Accommodation and Food Service Activities. As numerous fast food chains expand their businesses in various areas such as Metro Manila, more and more Filipinos are enticed to consume fast food products. Fast food chains seem to keep up with the increasing demands of the public for inexpensive and accessible food. The ASPBI reports that fast-food chains led second in the formal sector with a total of 4,477 establishments. That is 16.6% of the formal sector.

The fast food industry has been growing over the past few decades and has become a global phenomenon. Companies such as Mcdonald's, Starbucks, Subway, KFC, and Pizza Hut, the top ten most valuable fast food brands worldwide last 2017 (Statista, 2018), are dominating the global market. According to Statista, the brand value of Mcdonald's reached about 97.72 billion dollars in 2017, which had a 10.23 percent growth from its value of USD 88.65 billion the previous year. Indeed, the fast-food industry is growing at a fast rate, with the global fast food market being valued at more than USD 539 billion in 2016, and estimated to grow to around USD 690 billion in 2022 (Zion Market Research, 2017).

In the Philippine context, out of all the food service establishments in 2009, fast food outlets take up nine percent of independently owned establishments and 90.59 percent of the franchised or chained establishments (National Tax Research Center, 2013). In 2012, the Census of Philippine Business and Industry (CPBI) reports that the food service industry is valued at around USD 7.2 billion which has grown at 15 to 20 percent in the past decades (IFEX Philippines, n.d.). As of 2012, Transactions in the Philippine Fast Food market drastically changed by 28.23 percent from 2005-2010 and was expected to change by 12.58 percent from 2010-2015 (National Tax Research Center, 2013). Notable participants in the fast food industry include Jollibee, McDonald's, Chowking, Mang Inasal, KFC, and Greenwich. In fact, Jollibee has been consistently leading among its competitors, and is recognized as the largest fast food chain in the Philippines, according to their website. As of May 2017, Jollibee Food Corporation, which also handles other fast food brands such as Chowking and Red Ribbon, had 3555 stores worldwide and penetrated seventeen countries (Dumlao-Abadilla, 2017). Of these 3555 stores, 1000 of these stores can be attributed to Jollibee within the Philippines alone, which exhibits the aggressive nature of the fast food industry in the country.

According to the National Center for Health Statistics, from 2009-2010, 35.7 percent of US adults were obese while 16.9 percent of the children and adolescents were obese, which corresponded to 78 million and 12.5 million Americans, respectively (National Center for Health Statistics, 2012). In 2014, the Philippines had a prevalence of overweight of around 20 while around 5 percent for obesity among Filipinos (Domingo, 2016). The prevalence of obesity and overweight Filipinos were then linked to a change in diet of Filipinos over the years– one where higher-fat diets were becoming more rampant as well as an increase in consumption of processed foods and refined carbohydrates. These rises in obesity and calorie intake were coincident with the rise in fast food consumption in both the US and the Philippines.

Fast foods are often linked to obesity, and this can be supported by an article by Dr. Ananya Mandal, where she notes that fast foods contain high levels of calories, fat, saturated and trans fat, sugar, simple carbohydrates, and salt. She also discussed that people who eat fast food tend to have a higher body mass index (BMI), due to the unhealthy and lower quality of food choices in fast foods. Dr. Mandal further explained that children are more prone to obesity and are thus more affected by fast food consumption and eating out. Lastly, she also pointed out that home cooked meals had 55 percent lower calorie content than meals out-of-home meals.

This study aims to expose the relevant factors to the probability a student eats at a fast food restaurant in order to help improve the current state of fast food consumption and obesity in the Philippines. This can be done by performing Factor Analysis. Tests for association can also be done to analyze the relationship between these identified factors and the probability of a student eating at a fast food restaurant. Finally, a logistic regression model should be formed in order to analyze the odds of fast food consumption.

The researchers hope that the results of this study would help the government or other institutions in improving or creating health policies and regulations to monitor or lessen the fast food consumption of young adolescents. This study was also conducted so that appropriate programs may be conducted to gear young adolescents into having a healthier lifestyle. These objectives are to be met using the data from the Global School-based Student Health Survey (GSHS) conducted in the Philippines in 2011. From this, a model will be created to determine the possible influencers to the frequency of fast food visits of a student.

2 Review of Related Literature

2.1 Fast food and the human body

One of the common topics linked to health is the nutritional aspect of the food consumed by people. Fast food tend to have a higher saturated fat, sugar, salt, and calorie content (Hellesvig-Gaskell, 2017). Foods high in saturated fatty acids have been linked to cardiovascular diseases, or CVDs (Nettleton, et al., 2017), while those high in sugar are frowned upon by nutritionists due to their link to weight gain, as well their ability to deliver "empty calories" which are unaccompanied by other nutrients such as fiber and vitamins (Corliss, 2014). A systematic review of previous studies conducted by two researchers, however, notes that only excessive intake of foods high in sugar may increase the risk of weight gain and even CVDs (Khan and Sievenpiper, 2016).

In recent years, some fast food chains and suppliers have tried to address the health concerns associated with eating their products, in hopes of bringing in or maintaining profit for these entities. McDougal (2018) reported that a poultry supplier in the United States plans not to use drugs for growth promotion in raising poultry and livestock. This is to address the growing demand for healthier alternatives, such as organic and antibiotic-free poultry products.

Food preferences of people tend to get affected by their lifestyle. Social norms have been shown to influence the development of obesity among people caused by excessive consumption of unhealthy food (Higgs and Thomas, 2016). Thus, a suggestion was made to target these social eating norms to promote a more health-conscious lifestyle. People who regularly drink alcohol also tend to eat unhealthier food, as shown by researcher from the University of Liverpool (Ryan, 2016). The researchers also explained that this increased consumption of junk food is associated with how alcohol affects calorie inhibitory control, which is the ability of the human body to avoid craving high calorie food.

But regular consumption of fast food has also been shown to affect the dietary habits and preferences of consumers. Witherly (1999) postulates different theories on why people tend to get "addicted" to eating their favorite foods, most of which can be found in the menus of fast food chains. The so-called "Food Pleasure Equation" suggests that the human brain has the ability to "calculate" the pleasure that may be derived from eating certain foods based on their calorie content and maintaining the level of pleasure requires more food intake. Other theories mentioned suggest that food with certain texture and/or flavor contrasts and those with higher level of sugar, salt, and flavor-active compounds excite the receptors.

2.2 Fast food consumption among adolescents and students

The concept of ready-to-eat food is particularly aimed at people who cannot allot a significant amount of time to prepare, cook, and consume a "traditional family dinner." Thus, it does not come as a surprise that students are one of the top consumers of fast food. Cross-cultural and behavioral studies have been conducted to see what makes student prefer fast food, yielding similarities and differences.

College students in the midwestern region of the United States, as discussed by Abraham, et al. (2018), also showed preference for fast food when socializing. Students in the study also seem to agree that consumption of fast food contributes to likelihood of obesity, implying that the students are well aware of the health effects. In fact, one study points to availability as the culprit behind frequent fast food consumption. Denney-Wilson et al. (2009) conducted a cross-sectional survey made up 2,719 adolescents from Australia where students gave information on soft drink and fast food consumption. It was reported that 40% of them usually had soft drink available in their homes along with the fact that they would choose drinking this beverage over water or milk. In relation to fast food consumption, convenience and value for money were strongly associated with fast food consumption among boys while preference for fast food over home cooked meals and order upsizing were strongly associated with fast food among girls.

Most fast food companies rely on advertising to lure more people to buy their products. One research shows that advertising helps fast food penetrate both elementary and high school cafeterias in the United States (American Heart Association, 2014). The study explains that reaching school is a big step for these companies since it seems to be the only way for them to reach all students and to create “lifelong customers.”

2.3 Models used in predicting fast food visit

Majority of studies on fast food visits use modelling to predict fast food visits. For example, in a paper by Denney-Wilson et al. (2009) students were asked about their background on soft drink and fast food intake each day. The categories used were “I don’t drink soft drink”, “less than 250ml”, “between 250 and 400 ml”, “between 400 ml and 1 Liter”, and “more than 1 liter”. They were asked “how many days each week do you usually eat food from a fast food outlet” with the categories “Never or rarely”, “Less than once/week”, “about 1-3 times/week”, “about 4-6 times/week”, and “every day”. Other questions examined personal influences, social influences, and environmental influences. Multiple logistic regression was then performed to analyze the association between attitudes and consumption. Separate models were made for each level of any significant effect modifier. They then used a backward variable selection procedure to determine the factors significantly associated with consumption.

In a study by Poti et al. (2013), the association between fast food intake with poor dietary outcomes and obesity among children was probed. The objective of the study was to compare the various independent associations with overweight or dietary outcomes for fast food intake with dietary pattern for the remainder of consumption. They performed a cross-sectional analysis on 4466 US children aged 2-18. Cluster analysis was first performed and identified 2 dietary patterns for the non-fast food remainder of intake. Multivariable-adjusted linear and logistic regression models were then examined to examine the association between fast food consumption (FFC) and dietary pattern. The independent associations were then estimated with overweight and dietary outcomes.

A study by Xue, et al. (2016) on fast food consumption focused on its association with obesity among children, specifically in China. This was to study trends in FFC among Chinese children and the relationship between fast food consumption and obesity through national survey data. A linear regression model was fitted to examine the association between fast food consumption and Body Mass Index (BMI) z-scores in boys and girls, with BMI z-score as the response variable. Logistic regression was also done with children's weight status as the outcome.

3. Methodology

3.1 Collection of data

The data used in the study was obtained from the 2011 Global School-based Student Health Survey, a study conducted by the World Health Organization (WHO) that aims to help governments in different countries in providing a clearer picture of the current situation affecting students. Only the data from the survey held in the Philippines, which consists of 5,270 observations, was used in the analysis. A series of questions related to aspects of student life (such as diet, hygiene, and violence) were combined to create a self-administered questionnaire. The questionnaire was given to students coming from a mix of public and private high schools in the Philippines.

3.2 Description of variables

Dependent variable

The dependent variable, or the variable of interest, is the main focus of the study of which the researchers aim to explain or describe. In this study, the number of days in a week a student ate fast food is the dependent variable.

Independent variables

The independent variables are the observable quantities which will be used to explain or describe the dependent variable. The list of independent variables includes demographic-related questions (Age, Sex, Weight, Height, and Year Level), and questions related to different aspects of student life. These questions were considered categorical and were subjected to factor analysis.

3.3 Factor analysis

Factor analysis is a method that can be used to group variables based on some degree of association or based on their shared variation. The main goal of factor analysis is to attempt to estimate the covariance matrix Σ to see if it follows a prescribed structure. Thus, factor analysis can be viewed as a method to derive the "factor," or a construct behind a subset of variables that may explain the interrelationship between these variables. It can also be viewed as an extension of principal component analysis (PCA), another method used to attempt to estimate the covariance matrix (Johnson & Wichern, 2008). In factor analysis, an orthogonal factor model expresses the p variables as a function of m common factors, which are assumed to be unobservable, as well as p specific factors or error terms. Each variable has a loading on the common factors present; variables with high loadings under a factor tend to group together under that factor.

Due to the number and level of measurement of variables used in the study, factor analysis was necessary to reduce the number of covariates to be considered in the study. This also allowed the model to use continuous variables (in this case, the factor scores) as covariates, instead of the original categorical variables.

3.4 Generalized linear model

Overview

A classical linear model is one of the common models used in linear regression which aims to explain a dependent variable using a set of covariates (Agresti, 2013). It is of the form

$$Y_i=\beta_0+\beta_1 X_{i1}+\ \beta_2 X_{i2}+\ldots+\beta_k X_{ik}+\varepsilon_i$$

where Y represents the continuous dependent variable with values sampled independently from a population, the X's represent the covariates, the β's represent the coefficients that indicate the magnitude and direction of each covariate with respect to the dependent variable, and ε represents the error terms. Common assumptions which facilitate statistical inference include independence, homoscedasticity, and normality of error terms. Usually, problems with two or more assumptions can be addressed through one solution.

Generalized Linear Models (GLM) can be identified based on its three components: a random component (the dependent variable), a systematic component (the linear combination of the parameters), and a link component (the link function). The GLM still assumes that the error terms are independent, identically distributed, and homoscedastic, but it permits the error terms to assume a non-normal distribution, as long as the distribution belongs in the exponential family of distributions. Distributions that fall under this family can be expressed as

$$f(Y_i\,|\theta_i\,)=a(\theta_i\,)b(Y_i\,)\exp\{Y_i|Q(\theta_i\,)\}$$

where $a(\theta)$ is a function involving only the parameter θ, $b(Y)$ is a function involving only Y, and $\exp\{Y|Q(\theta)\}$ is the function linking the dependent variable to the function of the parameter called a natural parameter. Examples of distributions that fall under this family include the Binomial, the Poisson, and the Negative Binomial distributions.

3.5 Model selection

Backward and forward selection are variable selection techniques (Agresti, 2013). Variable selection is a method of picking which variables to include in the model. It is a special case of model selection. Stepwise variable selection is a family of methods for including variables in a model sequentially.

Forward stepwise regression begins with a small model, takes into consideration all one-variable expansions of the small model, and proceeds to add the variable which is optimal depending on some criterion. This criterion could be of the lowest p-value, highest adjusted R^2, lowest Mallow's C_p, lowest AIC. Variables are added one at a time until the criterion stops improving or has reached its optimal value. Meanwhile, backwards stepwise regression starts with the largest model we are willing to use and keep eliminating covariates until the criterion will no longer improve.

4. Results

4.1 Factor analysis

Before modelling, factor analysis was conducted in order to reduce the number of variables. This was conducted using PROC FACTOR in SAS. The Kaiser-Guttman rule recommends that the number of factors to be extracted be equal to the number of factors having an eigenvalue of at least 1. Based on the Eigenvalues of the Correlation Matrix (see Figure 1), it was possible to have at most 11 factors. However, following the scree plot in figure 1, a total of 6 factors was recommended namely, 1) vice, 2) assistance, 3) injury or bullying, 4) hygiene, 5) active lifestyle, and 6) healthy diet.

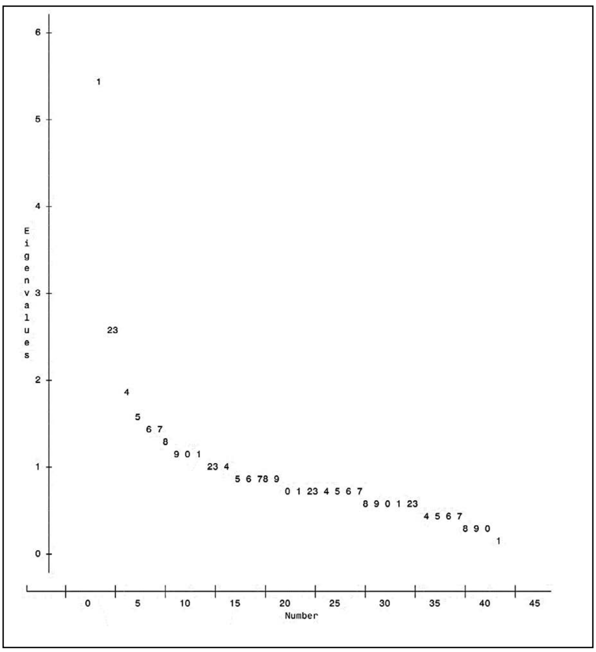

Figure 1. Screen Plot of Eigenvalues

To further verify the appropriation of factor analysis for the data set, the Root Mean Square Off-diagonal Residuals were examined. The resulting Root Mean Square Off-diagonal Residuals shows that the overall accuracy to be 0.05, and that the residuals for each of the variables are less than 0.07, thus the correlations among the variables is mostly explained by the factor model, reaffirming that factor analysis was appropriate. The factors obtained for weekly frequency of eating at a fast food joint with their respective variables that had significant loadings are presented in Table 1.

Table 1. Variables with Significant Loadings per Factor

Factor 1: Vice	**Factor 3: Injury or bullying**
Number_of_drinks_past_30_days	Times_attacked_past_12_mo_
Days_one_drink_or_more_past_30_days	Hungry30Days
Try_stop_smoking_past_12_mo_	Times_felt_lonely_past_12_mo_
Age_first_tried_cigarette	How_bullied_past_30_days
Times_drunk_during_life	How_many_days_bullied_past_30_days
Age_first_drink_of_alcohol	What_was_serious_injury_past_12_
How_many_days_smoked_30_days	Cause_of_injury_past_12_mo_
How_got_drinks_past_30_days	How_many_times_injured_past_12_mo
Number_of_troubles_as_result_of_drinking	
Others_present_smoking_past_7_days	**Factor 4: Hygiene**
Miss_school_no_permission_past_30_days	WashHandsEat
How_many_times_in_fight_12_mos	How_many_times_per_day_brush_tee
Other_forms_of_tobacco	SoapHands
Times_could_not_sleep_past_12_mo	WashHandsToilet
How_many_times_attempt_suicide_1	
Parents_who_use_tobacco	**Factor 5: Active lifestyle**
	Days_active_60_min_plus_past_7_days
Factor 2: Assistance	Time_spent_sitting_on_usual_day
Parent_understand_troubles_past_	
Parent_know_what_you_do_past_30_	**Factor 6: Healthy diet**
Parents_check_homework_past_30_days	Eat_fruit_per_day_past_30_days
Parent_go_through_things_past_30	Eat_vegetables_past_30_days
Others_helpful_in_school_past_30	Drink_soft_drinks_past_30_days
Days_went_to_PE_each_week	Number_close_friends
Walk_or_bike_to_school_past_7_days	

The first factor pooled together factors concerning alcohol, smoking and troubled experiences of a student. Troubled experiences include mental health, sleeping, and school attendance problems. This factor was then appropriately named the "Troubled Youth Factor," and is responsible for explaining the most variance in the factor model.

The second factor accounts for the guidance students receive from their parents and others in school. Overall, the second factor is more about the assistance from others a student receives which is why the factor is labelled the "Assistance Factor."

Injury and bullying variables were what comprised the third factor, with the addition of the variables pertaining to if a student went hungry in the past month, and if they felt lonely in the past year. All these variables cause harm to a student's well-being, whether physically or mentally, thus the factor was labelled "Harmful Experiences Factor."

Under the fourth factor are variables pertaining to the hygiene habits of a student, namely if they wash their hands before they eat, soap their hands, wash their hands after using the toilet, and the number of times they brush their teeth in a day. Thus, this factor was referred to as the "Hygiene Factor."

The fifth factor is comprised of only two variables: the number of days a student was active in the past week, and the time they spent sitting on a usual day. Both variables measure the degree of how active a student is, and thus the factor was named "Active Lifestyle Factor."

The last factor is composed of variables measuring the diet of a student such as their fruit, vegetable, and soft drinks consumption, and the number of close friends they have. This factor is also seen in Table 2. that it explained the least variance in the factor model. Since the presence of friends may have an effect on the food intake of an adolescent (Salvy, Elmo, Nitecki, Kluczynski, & Roemmich, 2011) then the number of close friends may also have an effect on a student's diet. Thus, the factor was named "Diet Factor."

Table 2. Variance Explained by Each Factor

Factor	Variance Explained
Troubled	5.3643765
Assistance	2.5917271
Harmful Experiences	2.5349499
Hygiene	1.8865099
Active Lifestyle	1.5922630
Diet	1.4953978

The scores of the observations for each factor was obtained and used as the covariates in the modelling process. Additional variables used in the modelling process include the demographics-related variables that were originally excluded from the factor analysis.

4.2 Descriptive statistics

A total of 3185 observations were used in the model building process when factor scores are used as predictors, after subjects with missing values for variables in consideration were removed. The response variable (*Y*), the number of times a student ate in a fast food restaurant in the past week, was first examined using the said dataset and its descriptive statistics were obtained, as shown below.

Table 3. Descriptive Statistics of *Y* – Basic Measures

Basic Statistical Measures			
Location		**Variability**	
Mean	0.666562	Std Deviation	1.08204
Median	0.000000	Variance	1.17082
Mode	0.000000	Range	7.00000
		Interquartile Range	1.00000

Looking at Table 3, the standard deviation, 1.0820 is greater than the mean that is 0.6666. This is a sign of overdispersion and hints on the use of the negative binomial distribution rather than the Poisson distribution for the model. The response variable *Y* tells us that there are more students who did not eat fast food in the past week versus those who did. Of those who did, approximately 66% of those had fast food once in the past week.

The characteristics of the predictors and their relationship with the response variable were also examined before moving on to the model building process. Upon getting the summary statistics of the weight of the respondents, the mean was found to be around 46 kilograms, with values ranging from 28 to 164 kilograms.

For each variable, the different levels of the number of days in a week a student ate fast food produced varying distributions of the variables, thus all the continuous variables may have a significant effect on the response variable and should be retained for model building. To further examine their relationships, a linear regression was done to predict the number of days in a week a student ate fast food using the seven continuous exploratory variables.

Table 4. Results of the Linear Regression of Continuous Variables for Predicting Y

	Estimate	t-value	p-value
(Intercept)	0.175705	1.805	0.071226
Factor1 – vice	0.055438	2.749	0.006011
Factor2 – assistance	0.078466	3.966	7.49e-05
Factor3 – injury or bullying	0.006872	0.346	0.729719
Factor4 – hygiene	0.021507	1.078	0.281338
Factor5 – active lifestyle	0.111981	5.647	1.79e-08
Factor6 – healthy diet	0.068312	3.430	0.000613
Weight	0.010670	5.091	3.79e-07

Examining the p-values of the estimates for each variable in Table 4, only factors 3 (injury or bullying) and 4 (hygiene) are not significant at 0.05 level of significance. Thus, it can be said that they do not significantly affect the number of days in a week a student ate fast food and should no longer be included in the model building process. The other variables proved to be significant and must be retained for modelling.

For the categorical explanatory variables, individual Chi-Squared tests of independence were conducted at 0.05 level of significance to test if they were independent of the number of days in a week a student ate fast food. Table 5 shows the p-values for each variable tested against the dependent variable.

Table 5. p-values for the Chi-Square test of each Discrete Explanatory Variable

Variable	p-value
Sex	0.0013
Binage	0.0002
Height	0.0604
YrLevel	<0.0001

As seen in Table 5, all the categorical variables except Height have p-values less than 0.05, thus all variables except for Height have a relationship with the number of days in a week a student ate fast food. The variable Age, which has six levels ranging from 1 (11 years old or younger) to 6 (16 years old or older), was evenly divided to create a binary variable. The resulting variable, Binage, took on a value of 0 if the age of the respondent was 13 years old or lower, and 1 if their ages were 14 or higher. Since Height was found to be independent of the number of days in a week a student ate fast food, it was also disregarded as a predictor in the model.

4.3 *Count model fit*

The researchers compared the fit between a Poisson log-linear and negative binomial model. The results of the criteria for assessing goodness of fit are as follows:

Table 6. Comparison of Models by Criteria for Assessing Goodness of Fit

Criterion	Poisson			Negative Binomial		
	DF	Value	Value/DF	DF	Value	Value/DF
Deviance	3406	4457.5286	1.3087	2924	2635.1734	0.9012
Pearson Chi-Square	3406	5772.8983	1.6949	2924	3348.2814	1.1451
AIC		7656.7374			6434.1332	
AICC		7656.7797			6434.1948	
BIC		7705.8225			6487.9841	

The model fits the data well if the deviance to degrees of freedom (df) is close to one. Based on results in Table 6 the Value/DF for Deviance is 1.3087, thus the model is adequate. The Pearson chi-square statistic can be used to assess the model's form. Since the Value/DF for Pearson Chi-Square is closer to 2, the data seems overdispersed. Comparing the goodness of fit criteria of the Poisson Log-Linear Model to the Negative Binomial model, it can be shown that the latter model is more suitable for the data. The Deviance/DF value for Negative Binomial is only 0.0988 units away from 1. In addition, the AIC, AICC, and BIC for the Negative Binomial model are smaller compared to that of the Poisson Log-Linear model. The Negative Binomial model therefore was deemed to have a better fit for the data. The final model is presented in the succeeding section.

4.4 *Discussion of count model for weekly eating frequency at a fast food joint (Y)*

Table 7. Analysis of Maximum Likelihood Parameter Estimates

Parameter		Estimate	Pr > ChiSq
Intercept		-1.4803	<.0001
Sex	Female	0.2300	0.0002
Sex	Male	0.0000	.
Binage	0	0.2892	<.0001
Weight		0.0177	<.0001
Factor1 – vice		0.1166	<.0001
Factor2 – assistance		0.1035	0.0003
Factor5 – active lifestyle		0.1576	<.0001
Factor6 – healthy diet		0.0764	0.0073
Dispersion		0.8371	

Table 7 displays the coefficient estimates and associated p-values. The coefficients for Sex, Binage, Weight, Vice, Assistance, Active lifestyle, and Healthy diet are all statistically significant. The coefficients for factors, injury or bullying and hygiene have been omitted from the table since they are not statistically significant. None of the variables have a negative effect on the response implying that all variables increase the weekly frequency of eating at a fast food chain. The final model is interpreted in the following manner: The variable dispersion has a coefficient of 0.8371 units. It also has a Wald 95% confidence interval (omitted from the table) of (0.7052,0.9937), which does not contain 0. This means that the Negative Binomial model is a good fit for the data. The estimate is also greater than zero, therefore there is overdispersion in the model.

The variable Sex has a coefficient of 0.23 for females. This means that being a female versus being a male increases the log odds of weekly eating frequency at a fast food chain by 0.23 units. Females are known to have higher BMI than males. This is supported by the study of Mandal (2017) where it showed that higher BMI is associated with higher fast food consumption, females must consume more fast food than males. The model affirms this with its estimate for the coefficient. This however contradicts other studies which state that females are more conscious of their food choices making them less likely to consume fast food (Persaud, 2006).

The indicator for Binage = 0 is the expected difference in log count between children aged 13 below and teens aged 14 above. The variable Binage has a coefficient 0.2892 for Binage = 0. This means that children aged 13 and below increase the log odds of weekly eating frequency at a fast food chain by 0.2892 units. The estimate is positive implying that children aged 13 and below, have an increased chance of eating more often at a fast food restaurant every week. This could be because most fast food commercials in the Philippines consist of children enjoying fast food with their family. This could desensitize families of the dangers of eating fast food often.

The variable weight has a coefficient of 0.0177 units which is statistically significant. This means that for each one-unit increase in variable weight, the expected log-count of the weekly eating frequency at a fast food chain increases by 0.0177 units. The increase in the response from this variable is minute so the impact of weight on the response could be negligible. It has the least effect on the response variable. However, this existing relationship in the model could be linked to the association between dietary energy density and its supposed impact on body weight (Pangan et al., 2012).

The variable Factor1 referring to vices has a coefficient of 0.1166 units. This means that for each one-unit increase in variable Factor1, the expected log-count of the weekly eating frequency at a fast food chain increases by 0.1166 units. Although it is not a large increase, a study by Heydari et al. in 2014 revealed that smokers more frequently dined in fast food restaurants compared to non-smokers. Moreover, Lloyd-Richardson et al. (2008) released research regarding the relationship between alcohol consumption and an unhealthy diet in freshman college students. The results conclude that the more one drinks, the more likely they are to consume food after the drinking session, thus resulting in higher BMI after one semester. It is plausible that under the influence of alcohol, the subjects reach for fast food instead of self-prepared or expensive food.

The variable Factor2 referring to the assistance obtained from others has a coefficient of 0.1035 units. This means that for each one-unit increase in variable Factor2, the expected log-count of the weekly eating frequency at a fast food chain increases by 0.1035 units. The variable could be significant in the model because parents directly influence the eating patterns of a child even during its fetal stage (Savage et al., 2007). One plausible explanation for the positive coefficient estimate is that the parents of the child could also be frequent consumers of fast food and therefore encourage their child to consume this kind of food also.

The variable Factor5 referring to the activity level has a coefficient of 0.1576 units. This means that for each one-unit increase in variable Factor5, the expected log-count of the weekly eating frequency at a fast food chain increases by 0.1576 units. The researchers expected this coefficient to be negative since higher activity level would indicate a healthier lifestyle. However, a study by Dmitruk et al. (2016) suggests that boys who had a more active lifestyle tend to consume more whole wheat bread, meat, and fast food or calorie dense food.

The variable Factor6 referring to diet has a coefficient of 0.0764 units. This means that for each one-unit increase in variable Factor6, the expected log-count of the weekly eating frequency at a fast food chain increases by 0.0764 units. Note that even though diet intuitively affects fast food consumption, the coefficient for this factor is small. This questionable outcome could be because the questions in the 2011 GSHS were mostly focused on consumption of healthy food and sugary drinks. Although it is intuitive to think that consumption of healthy food means avoiding fast food, this is not the case. It is still feasible for a subject to consume healthy food and fast food as part of their regular diet. The slight increase in fast food consumption indicated by the sign of the coefficient estimate could be attributed to the variable within the diet factor referring to consumption of sugary drinks. This is because most fast food meals are accompanied by unhealthy sugary drinks instead of water or real fruit juice.

4.5 Binary logistic model using factor scores

As seen in the earlier descriptive statistics of the response variable, 1308 students ate at a fast food chain at least once in the past week while 1876 did not. Both figures are quite close to each other indicating an almost balanced dataset. This prompted for further investigation, thus a binary logistic model for a recoded response variable was explored.

Tests for association

Multiple Chi-square tests for association were run for each factor variable and the response variable Y. But due to the inappropriateness of the test for the variable Other_forms_of_tobacco, the Fisher's Exact Test was used instead. For the following variables: How_many_times_in_fight_12_mos, What_was_serious_injury_past_12, Days_one_drink_or_ more_past_30_d, and How_got_drinks_past_ 30_days, both the Chi-square Test for Independence and Fisher's Exact Test could not be used, because of their inappropriateness for the data. Below are the p-values of the variables that were found to be independent of whether a student ate in a fast food chain in the past week, at a 0.05 level of significance.

Table 8. Tests for Association P-values for Variables Independent of the Frequency of Eating at a Fast Food Chain

Variable	P-value
How_many_days_bullied_past_30_da	0.502164
How_bullied_past_30_days	0.950759
How_many_times_attempt_suicide_1	0.125782
Number_close_friends	0.2357
Age_first_tried_cigarette	0.526046
How_many_days_smoked_30_days	0.529402
Try_stop_smoking_past_12_mo_	0.276913
Miss_school_no_permission_past_3	0.891214
Others_helpful_in_school_past_30	0.101275
Parent_understand_troubles_past_	0.113557
Parent_know_what_you_do_past_30_	0.360014
Other_forms_of_tobacco	0.1919

From Table 8, out of the initial forty-seven possible predictors, twelve of them were found to be independent of whether or not a student ate at a fast food chain in the past week, thus the number of predictors for modelling can be reduced to the remaining thirty-five variables that may be dependent on the response variable. This reduction in variables made it easier for modelling, as less predictors were considered, which provided for a simpler initial model.

Initial model

As mentioned in the previous section, the number of predictors were reduced to thirty-five variables. The first model that was run in R included all those predictors, with Y as the response variable. As expected, the model was overfitted, with some occurrences of fitted probabilities of 0 or 1. Although this was the case, it provided an AIC of 2694.5, and a residual deviance of 2378.5 which was significantly different from that the null deviance of 2944.5. The Deviance/DF of the model was 1.2098, which is quite close to 1 indicating an almost good fit of the model. But due to the overfit of this model, various variable selection procedures were tried to filter out the non-significant variables for predicting Y.

The following variables were insignificant to model the frequency of eating at a fast food chain at a 0.05 level of significance: Binage, Others_present_smoking_past_7_da, and Parent_go_through_things _past_30. Thus, a new model was built without these variables. Running the analysis of deviance on the new model, it was found that all variables were now found to be significant. The AIC, although a bit higher than the initial model, is still acceptable, because at least this model contains only the variables that are truly significant in predicting Y. This final model included the following variables:

> Drink_soft_drinks_past_30_days, Time_spent_sitting_on_usual_day, Eat_fruit_per_day_past_30_days, YrLevel, Weight, Days_went_to_PE_each_week, Hungry30Days, What_was_serious_injury_past_12_, Sex, Walk_or_bike_to_school_past_7_da, Times_could_not_sleep_past_12_mo, Age_first_drink_of_alcohol, and Parents_check_homework_past_30_d

Looking at the predictive accuracy of the final model from the forward selection, a threshold of 0.5 results in at least 60% of sensitivity, specificity, and overall accuracy in the model. A threshold of 0.4 increases the sensitivity of the model in expense of its specificity, and the opposite is true for a threshold value of 0.6.

Now, using the backward selection procedure resulted in a saturated model in which all the predictors are included in the model. From that model, variables are removed until the best model in terms of AIC is achieved. The resulting model had an AIC of 2620.6, which is the same as that of the result of the forward selection model, and a Deviance/DF of 1.2050, which is close to one indicating an approximately good fit.

The predictive accuracy was measured the same way as the models in forward selection, by using the test dataset. The results of the backward selection showed a similar trend in the predictive accuracy measures of the model with that of the final model using forward selection. The sensitivity-specificity trade-off also quite prominent in this model as we raise the lower the threshold to 0.6 and 0.4, respectively. A threshold of 0.5 is still the most desirable since it has values of at least 60% in all of its prediction accuracy measures.

Best model selection

The two models under consideration for the best model were the two final models under forward and backward selection. Although they did not have the lowest AIC among all the models generated, all the predictors involved in each model had at least one level per variable that had a significant estimate. Among the models that possessed this characteristic, these two models were found to have one of the lowest AICs. It must also be noted that all the variables included in the models are significant at a level of significance of 0.05, using the analysis of deviance test, as seen in the previous discussions. Table 9 shows the vital information for both models for comparison.

Table 9. Forward vs Backward Final Models Key Aspects

	Selection Procedure	
	Forward	**Backward**
No. variables	13	14
AIC	2639.5	2639.5
Residual Deviance	2521.5	2513.5
DF	2065	2061
Deviance/DF	1.221065	1.219554
Hoslem p-value	0.7146	0.6923
Sensitivity (0.4)	0.7457627	0.7457627
Specificity (0.4)	0.4885496	0.5053435
Overall Accuracy (0.4)	0.5278137	0.542044
Sensitivity (0.5)	0.6271186	0.6271186
Specificity (0.5)	0.659542	0.670229
Overall Accuracy (0.5)	0.6545925	0.6636481
Sensitivity (0.6)	0.4915254	0.4830508
Specificity (0.6)	0.7938931	0.7984733
Overall Accuracy (0.6)	0.7477361	0.7503234

Checking for goodness of fit measures, both models have the same AIC and very close values for their Deviance/DF, with the final backward selection model having a value a little closer to one, thus indicating a slightly better fit. Another test that was considered was the Hosmer-Lemeshow Test, with a null hypothesis of the model being a bad fit, and the alternative hypothesis of being a good fit. Both models have p-values greater than 0.05 indicating a good fit for both, with the final model using forward selection having a higher p-value and showing greater evidence against the model being a bad fit. Since the goodness of fit procedures were tied for the decision of which model was better, it came down to the predictive accuracy of the models, which included examining each one's ROC curve, area under the curve (AUC), Sensitivity, Specificity, and Overall Accuracy.

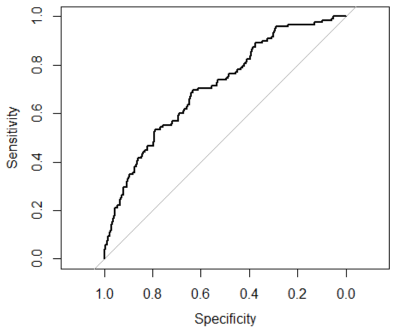

Figure 2a. ROC Curve for the Final Forward Selection Model

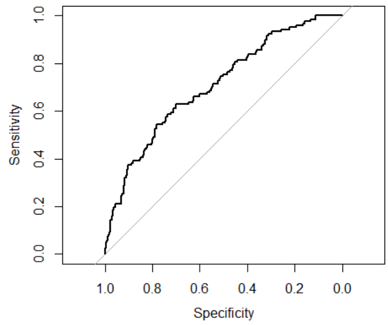

Figure 2b. ROC Curve for the Final Backward Selection Model

The ROC curves of both models look alike, and from them it can be estimated that the AUC is greater than 0.5 but less than around 0.75. In particular, the final model under forward selection had an AUC of 0.7096 while that of backward selection had an AUC of 0.7077. The difference in AUC is very minimal, with the final model under forward selection having a slight edge over the other final model under backward selection. Looking at the Predictive accuracy measures with threshold value of 0.5, both models have the same Sensitivity at 62.71%, but the final model under backward selection has a higher Specificity and Overall Accuracy at 67.02% and 66.36%, respectively. Thus, the final model under backward selection will be used as the best model for predicting whether a student ate in a fast food chain in the past week (Y).

4.6 Final model interpretation

The final model is composed of fourteen predictors, all of which with at least one level significant at a level of significance of 0.05, as seen in Table 10.

Looking at the p-values in Table 10, it can be said that the frequency of drinking soft drinks may be one of the most important predictors for explaining the fast food intake of a student.

The Weight variable in the model can be interpreted as if a student is one kilogram heavier, they are 2.5% more likely to eat in a fast food chain. This positive relationship was very intuitive because there have been many studies linking fast food intake to weight gain and obesity. In a study by Bowman and Vinyard (2004), it was found that adults who ate fast food had a higher mean body mass index, with an increase in energy density and a corresponding drop in micronutrient density, which may all contribute to the weight gain of an individual.

Table 10. Significant Variables of the Final Model

	Estimate	Exp(Estimate)	Pr(>|z|)
(Intercept)	-2.55139	0.077973	2.80E-09
Weight	0.024692	1.024999	1.47E-05
SexMale	-0.41315	0.661562	8.61E-05
YrLevel2	-0.60075	0.548402	1.13E-05
YrLevel4	-0.65771	0.518038	6.93E-05
Hungry30Days2	-0.26445	0.76763	0.038606
Hungry30Days3	-0.66397	0.514805	5.66E-08
Hungry30Days4	-0.72658	0.48356	6.60E-03
Eat_fruit_per_day_past_30_days2	0.947863	2.58019	0.001078
Eat_fruit_per_day_past_30_days3	1.018351	2.768626	0.000378
Eat_fruit_per_day_past_30_days4	1.331663	3.787336	6.48E-06
Eat_fruit_per_day_past_30_days5	1.460802	4.309414	2.64E-06
Eat_fruit_per_day_past_30_days6	1.153793	3.170195	4.76E-03
Eat_fruit_per_day_past_30_days7	0.84179	2.320517	2.36E-02
Drink_soft_drinks_past_30_days3	0.93256	2.541006	3.11E-06
Drink_soft_drinks_past_30_days4	1.206016	3.340151	1.28E-07
Drink_soft_drinks_past_30_days5	1.495226	4.460344	8.38E-07
Drink_soft_drinks_past_30_days6	1.774997	5.900263	0.001868
Drink_soft_drinks_past_30_days7	1.83704	6.277928	7.85E-05
What_was_serious_injury_past_12_2	0.622351	1.863304	0.005832
What_was_serious_injury_past_12_3	0.676988	1.967941	0.004288
What_was_serious_injury_past_12_8	0.456739	1.578917	2.81E-03
Times_could_not_sleep_past_12_mo3	0.37983	1.462036	0.005342
Times_could_not_sleep_past_12_mo4	0.409944	1.506733	0.047139
Others_present_smoking_past_7_da5	-0.38456	0.680753	0.031249
Age_first_drink_of_alcohol5	0.586891	1.798389	0.000611
Walk_or_bike_to_school_past_7_da4	-0.56173	0.57022	0.025578
Walk_or_bike_to_school_past_7_da6	-0.43464	0.647498	0.008803
Walk_or_bike_to_school_past_7_da8	-0.52293	0.592783	0.000163
Days_went_to_PE_each_week5	-0.53501	0.585666	0.008736
Days_went_to_PE_each_week6	-0.47294	0.62317	0.010789
Time_spent_sitting_on_usual_day3	0.556497	1.744551	0.000137
Time_spent_sitting_on_usual_day4	0.601243	1.824385	0.003305
Parent_go_through_things_past_303	0.306811	1.359084	0.015127
Parent_go_through_things_past_305	0.617919	1.855064	0.004046

The model also implies that the odds of eating at a fast food chain for males are lesser than that of females by 33.84%. This relationship can be backed by a research done by Morse and Driskell in 2009, where the frequency of eating at fast food chains were significantly different for men and women. In a study by Patricia and Azanza in 2001, a survey conducted showed that the typical customer in a fast food restaurant was female, thus supporting the model estimate for sex.

The year level of a student, specifically whether or not the student is a freshman was also found to be significant in explaining the occurrence of fast food intake of a student. Specifically, a student in their first year has higher odds of eating at a fast food chain than a second year student by 45.16% and by a fourth year student by 48.2%. This may be because freshmen are still adjusting to high school life compared to those in their second and fourth years. This adjustment may include stress eating in fast food chains or going out with friends also in fast food chains since they provide for a cheaper place to eat. In a study by Deliens et al., it was found that the weight gained in freshman year in a university was strongly correlated to the initial weight of their roommate, indicating that a freshman's food choices may be strongly influenced by that of their peers (Deliens, Clarys, Bourdeaudhuij, & Deforche, 2014).

Another significant variable was whether the student felt hungry in the past 30 days due to lack of food in their homes. In fact, those who never felt hungry under the said conditions had higher odds of eating at a fast food chain by 23.24% of those who rarely feel hungry, 48.52% of those who sometimes feel hungry, and by 51.64% of those who feel hungry most of the time. Generally, the model shows that the more frequent a student feels hungry at home due to lack of food, the lower their odds of eating at a fast food chain compared to those who never feel hungry. This result is contrary to the logic that people who are have no food at home would tend to buy more fast food because it is seen as a convenient and cheap source of food. There may be an underlying variable that would explain this relationship which may not have been in the scope of the GSHS.

Certain aspects of a student's diet were also found to significantly affect whether they eat at fast food chains. These were the frequency of eating fruit and drinking soft drinks in a day within a 30-day period. From the model, the students who ate fruit at least once in the past 30 days had higher odds of eating at a fast food chain than those who do not. Specifically, odds of eating at a fast food chain are higher among those who eat fruit less than once a day, once a day, twice a day, three times a day, four times a day, and five or more times a day, by 158.02%, 176.86%, 278.73%, 330.94%, 217.02%, and 132.05% respectively, than those who do not eat fruit at all. It is most often thought that a person who includes fruits and vegetables in their diet are health conscious and would not opt for fast food. But it can also be those who eat fruit may feel very healthy, such that they would compensate this with eating unhealthy food, such as fast food. Soft drinks also pose a similar result, with those who never drank soft drinks having a lower chance of eating at a fast food chain than those who do not. Particularly, odds of eating at a fast food chain are higher among those who drink soft drinks once a day, twice a day, three times a day, four times a day, and five or more times a day, by 154.10%, 234.02%, 346.03%, 490.03%, and 527.79% respectively, than those who do not drink soft drinks at all. Soft drinks are usually thought to come hand in hand with fast food, since fast food meals usually come with soft drinks, thus those who drink soft drinks more frequently would be more inclined to buy from fast food chains since these drinks are usually paired with fast food meals. This may be why increased soft drink intake led to an increase in the odds of eating at a fast food chain.

The kind of the most serious injury a student experienced in the past month was also found to be significant in explaining whether they had fast food in the past week. If a student had a broken bone or dislocated joint, this increased their odds of eating fast food by 86.33% compared to those who were not injured. Odds of eating fast food went higher by 96.79% and 57.89% was also observed among those who had a cut or stab wound and having other sources of injury, respectively, compared to those who did not get injured. Injuries may cause people to feel incompetent and useless, thus fast food, being considered as comfort food, may be what these people resort to in order to lift their spirits.

The model estimates show that the odds of a student eating at a fast food chain are higher by 46.20% and 50.67% when they rarely and sometimes could not sleep at night in the past 12 months, respectively, than when they had no problems sleeping at night. This can be attributed to late-night purchases of fast food when a person cannot sleep at night. Additionally, a study by Greer, Goldstein, and Walker shows that sleep deprivation impacts one's brain in which individuals tend to desire weight-gain promoting high-calorie foods, such as fast food, than healthier choices (Greer, Goldstein, & Walker, 2013). An increase in fast food intake in the mornings may also play a role since students would no longer have time to eat at home since they slept late and are running late for school.

If people have smoked in a student's presence every day in the past week, the odds of a student eating at a fast food chain decrease by 31.93%, compared to if no one had smoked in their presence in the past week. A study has shown that smokers are reported to have more frequent cravings for fast food than non-smokers (Chao, White, Grilo, & Sinha, 2017). Being exposed to people smoking everyday may also have the same effect on those being exposed and increased their cravings for fast food as well.

Based on the model estimates, the age for first-time alcohol consumption also affects the odds of a student eating fast food. Subjects who drank alcohol during their transitioning years (i.e. pre-teen years) increased their odds of eating at a fast food chain by 79.83%. This could be related to the culture these children were accustomed to. If they were introduced to alcohol at an early age, they were likely unsupervised by their parents or were exposed to it by their parents. According to Majdabadi et al. (2017), a holistic approach in lifestyle change (culture, social support, and supervision) is promising effort when it comes to reducing FFC.

Activity level also affected the level of fast food intake. The model estimates suggest that walking or biking to school 3, 5, and 7 days a week decrease the odds of fast food consumption by 42.98%, 35.25%, and 40.72%, respectively. Moreover, the odds of FFC decrease by 41.43% and 37.68% when the student went to PE 3 and 4 times a week. That is 3 or 4 out of 5 school days. Meanwhile, the table of parameter estimates show that inactivity can lead to an increase in fast food consumption. According to the odds ratios for fast food consumption, the odds of fast food intake increase by 74.46% and 82.44% when the student spends their time sitting, watching television, playing computer games, and talking with friends whilst sitting down for 3-4 hours and 5-6 hours respectively. These odds further prove that lifestyle choices can affect fast food intake.

The act of going through your child's things "sometimes" and "always" can also increase the odds of fast food consumption by 35.91% and 85.51% compared to those who answered "never". This is due to intervening variables such as having vices because parents are more like to check their children's things when the child cannot be trusted. From the model and other studies mentioned, consumption of vices also increases the odds of fat food consumption.

Since the logistic regression model based on the actual variables yielded relatively high predictive accuracy measures and used direct information from the data unlike factor scores, this model was chosen as the final model.

5. Summary and Conclusions

The model created was focused on being able to predict which students would eat in a fast food chain, rather than those who do not, since they are the students who would need the most help lessening their fast food intake. Through this model, certain practices of children, such as their exposure to certain activities, people, and food could also be more controlled by their parents, and even by the community, to lessen the inclination for fast food consumption of adolescents.

One of the important takeaways from the model was the role of parents in the decisions made by their parents. In the Philippines, attitudes of mothers and fathers regarding parenting have been changing, with mothers slowly shifting to a Western, progressive attitude that allows for some degree of leniency (e.g. allowing children to freely express themselves) as compared to fathers (Alampay & Jocson, 2012). On the other hand, it was also noted that Filipino youth still value family as an authority-like figure, as shown by their adherence to the influence of their parents in decision making. Therefore, it may be easier for Filipino parents to persuade their children to adhere to a diet that depends less on fast food. Parents should take more care of their children's health while they are freshmen in their high schools, since that is when they would be most prone to eating fast food. They can do this by intervening in their diets, such us limiting soft drink intake of their children, and encouraging them to eat healthy food. Parents should also persuade their children to get enough sleep at night, since lack of sleep programs the body to eat more unhealthy food.

Schools have the responsibility in aiding in the development of the well-being of their students. Providing free or offering cheaper healthy alternatives to the students' usual baon can entice them to avoid eating unhealthy fast food. Schools may give out pamphlets to point the freshmen to restaurants or canteens that could provide healthier food services. Allowing students to partake in an active lifestyle by doing more physical activities such as walking, biking, and extra Physical Education (PE) classes may encourage students to avoid consuming unhealthy food.

Lastly, the government should be stricter in implementing rules against smoking in public areas, since exposure and participation in such activity also affects a student's tendency to consume fast food. The government can also spearhead campaigns on healthy lifestyles and diet especially in public schools near commercialized areas, where there are more likely to be fast food chains present.

The researchers recommend that other researchers look further into why eating fruits increase the odds of eating in a fast food chain, since this should have been an indicator of a healthy diet. Another topic to research more into is why a student who never feels hungry at home due to lack of food is more likely to eat fast food than those who do. It would also be recommended that more continuous variables be added as predictors, as well as interaction terms. The GSHS should include more questions regarding their socio-demographics, such as their family's income level and social class, to further improve the model should other researchers decide to recreate the study.

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