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Association Between Bisphenols, Acrylamide, Glycidamide, Fast Food, and Obesity: An Obesogenic Perspective

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This is to certify that the doctoral study by

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Walden University
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Abstract

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by

Morgan P. Murphy

MPH, Kent State University, 2018

BA, Hampton University, 2016

Doctoral Study Submitted in Partial Fulfillment

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Abstract

Endocrine disrupting chemicals (EDCs) are exogenous man-made substances that have the ability to interfere with hormone action and are believed to be a contributing factor to chronic illnesses, including but not limited to obesity. Recent studies have suggested that environmental agents (environmental obesogens), such as food additives, plasticizers, and personal care products are contributors that aid in the altering of hormone receptors and hormone mimicry. Such environmental obesogens have the potential to promote adipogenesis and fat accumulation. In this study the social ecological model was used to determine the factors that can influence increased exposure to obesogenic chemicals at the intrapersonal, interpersonal, organizational and community levels of an individual. This correlational cross-sectional quantitative study analysis of the National Health and Nutrition Examination Survey (NHANES) 2015–2016 cycle investigated the possible relationship between the dependent variable of body mass index (BMI) and the independent variables of bisphenols A, F, S, acrylamide (AA), and glycidamide (GA) while controlling for confounding variables that served as markers for each level of the social ecological model. Linear regression analysis indicated that the endocrine disruptors BPA and AA/GA were the only significant predictors of BMI ($p < 0.05$) among the confounding variables of income, race, food security, and times healthcare was received over the past year. This study can promote positive social change by offering insights on the levels of exposure to endocrine disruptors, which can be useful for longitudinal epidemiological and biomonitoring studies, conducted by national and international environmental agencies, for precautionary toxicological assessments in the future.

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Dedication

This paper is dedicated to my Mother and Father, Marian and Steven Murphy; thank you for always believing and loving me. I am, and will always be forever grateful of your compassion that made me the woman I am. I love you!

This paper is also dedicated to the little girl who had big dreams of being somebody. This paper is a testament to her resolve, courage, intelligence, and determination to succeed in any arena. Little girl, you are on your way to do great things! Continue to choose the hard work, don't stop, soar like the phoenix and shine bright like the whitest star. Never forget the passages that inspired you, William Blake's "Tyger, Tyger, burning bright, In the forests of the night; what immortal hand or eye, could frame thy fearful symmetry? In what distant deep or skies, burnt the fire of thine eyes? On what wings dare he aspire? What the hand, dare seize the fire?

Adding the immortal words of Dr. Seuss, "You have brains in your head. You have feet in your shoes. You can steer yourself in any direction you choose! And will you succeed? Yes! You will, indeed! 98 and ¾ percent guaranteed"!

Little girl, you have gone the distance, you found your way, you were strong; every mile has been worthwhile, and you are right where you belong. Dr. Morgan has got if from here.

Congratulations, Dr. Morgan Paige Murphy.

Acknowledgments

I would like to acknowledge and thank my God for blessing me with His everlasting grace and mercy; I would be nothing without Him. I would also like to express gratitude to my amazing Chair, Dr. Vasileios Margaritis, for his continuous support, knowledge, and patience. His guidance was instrumental in making sure that I kept the course with the doctoral capstone guidelines. Besides my Chair, I would like to thank Dr. Julia Leischner and Dr. Sanggon Nam for their insightful comments and encouragement. In addition, I would also like to thank my Doctoral Advocate, Jen Rothamel, for her abundance of compassion and communication. She has been a pilar of stability during the strenuous time of completing all steps concerning this milestone. Lastly, I would like to show thanks to the Walden University Administration, Faculty, and Staff for their instruction and resources.

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Section 1: Foundation of the Study and Literature Review

Introduction

Endocrine disrupting chemicals (EDCs), also known as endocrine disruptors, endocrine active compounds, endocrine materials, or specifically obesogenic compounds are defined as exogenous chemicals and sometimes mixtures of chemicals that mimic and interfere with normal aspects of hormone functioning (Yang et al., 2015). According to the United States Environmental Protection Agency (EPA), endocrine disrupting chemicals can specifically interfere with the synthesis, secretion, transport, metabolism, receptor binding, and the elimination of endogenous hormones, which in turn alter and compromise the endocrine and homeostatic systems of the body (Lauretta et al., 2019).

The endocrine system plays a pivotal role in the regulation of metabolism of fats, carbohydrates, and proteins for bodily energy; any alterations from the hormones can lead to an imbalance in metabolism, inappropriate deposits of fat, ultimately leading to obesity (Nasirullah, 2020). The incidence of obesity has reached an all-time high in recent years. The increase has been observed worldwide. Because of the alarming rates of obesity, there is a growing need to analyze and understand all factors that could contribute to the high incidence of obesity (Egusquiza & Blumberg, 2020). A considerable number of identified endocrine disrupting chemicals seem to interfere with the normal functions of the hypothalamus-pituitary-gonadal axis, which governs the reproductive system and is driven by the brain, however it is very possible that every endocrine axis may be a target for endocrine disruptors (Lauretta et al., 2019). Endocrine disruptors have capabilities that increase the likelihood of contracting negative health outcomes, including but not limited to various cancers, reproductive impairment, cognitive defects, and more commonly, obesity (Zlatnik, 2016). The development of many chronic metabolic diseases, such as obesity, may be the result of low dose exposures from environmental and manufactured toxicants (Gupta et al., 2020).

According to Hales et al. (2017), as mentioned in Egusquiza and Blumberg (2020), the incidence of obesity has reached an all-time high, with approximately 39.6% of American adults categorized as obese in 2016, compared to the 1980 statistic of 13.4%. Since there is a growing need to understand all possible factors that contribute to obesity, public health scientists and leadership must optimize all efforts to prevent further incidences of obesity through the analysis of associated comorbidities, which involves the basis of the obesogen hypothesis (Heindel et al., 2017). The obesogen hypothesis alludes to how there are chemicals in the human environment (obesogens) that can affect individual susceptibility to obesity, which would explain the high rates of obesity (Egusquiza & Blumberg, 2020).

Though endocrine disruptors are still considered a relatively new field of study, significant strides have been made to advance the understanding between the chemicals and obesity. Such strides in advancement have determined that endocrine disruptors need to be identified and categorized. In order to determine if a solidified positive association between specific endocrine disruptors and obesity through body mass index (BMI) can be made, the analyzing of bisphenol A (BPA), its analogues of bisphenol S (BPS) and bisphenol F (BPF), acrylamide (AA) and glycidamide (GA) and obesity took place. Recent reports suggest that urinary BPA and its analogs of BPF and BPS correlate with obesity, but the lack of definitive proof has yet to be seen (Jacobson et al., 2019; Liu et al., 2017). Other recent developments suggest that AA and GA may have obesogenic properties that may contribute to increased peroxisome proliferator-activated receptors γ (PPARγ) expression, which affects adipose (fat) tissue, very few studies have examined the possibility of acrylamide or glycidamide being considered endocrine disruptors or obesogenic chemicals.

Continued research on the aforementioned endocrine disruptors will lead to significant policy changes and improvements in obesity reduction and health behaviors. Possible policy recommendations include: (a) the consensus of endocrine disrupting chemical identification and definition, (b) consensus on the evaluation of endocrine disrupting chemicals, (c) the development of an agency that will be specialized for research on endocrine disruptors, and (d) the mandatory provision of chemical composition for marketed substances (Kassotis et al., 2020).

Another possible change to policy is the taxation of junk/fast food, which could contribute to the intake of environmental endocrine disruptors. A study conducted by Blakely et al. (2020) demonstrated that a tax on sugar sweetened beverages and junk foods from the Mexican government seemed to produce great health gains. The eight percent junk food tax had modest effects which lead to the increase of vegetables and a noticeable decrease in saturated fats and sugars (Blakely et al., 2020). Due to the success of the junk food tax, the same could be applied to fast food in an attempt to reduce the intake of endocrine disrupting chemicals that are located in highly processed foods. However, with the implementation of a fast food tax, a subsidy on unsaturated foods such as fresh fruits and vegetables should be developed (Krishnamoorthy et al., 2020). In this section I will discuss the problem statement, purpose, research questions, nature, definitions, theoretical framework, and significance of the study. I will also discuss the literature review related to key variables and/or concepts of the study.

Given the nature of this topic, additional information is bound to improve the development of healthy changes for the United States and worthy research in public health, political, medical and scientific arenas. Possible positive social change implications that relate to the examination of these endocrine disrupting chemicals include the following modifications: communication with the Word Health Organization, European Commission and European Parliament, institutions who are well adept in the subject matter of endocrine disrupting chemicals specifically since they are the forefront of policy legislation such as REACH Regulation (Registration, Evaluation, Authorization and Restriction of Chemicals); lower healthcare costs that can effect employees, employers, medical expenses and productivity for the better and can contribute to increasing gross domestic product; closing the gap on racial and ethnic disparities associated with chronic diseases; and lastly an overall healthier society with the promotion of healthier lifestyles through lower incidences of dysfunction and disease, specifically obesity.

Problem Statement

Obesity is a disease that continues to reach worldwide proportions, and has continued to increase within the past 5 decades (Srour et al., 2019). Exposure to endocrine-disrupting chemicals (obesogenic chemicals) through foods and beverage consumption, inhalation, and dermal exposure have contributed to the global health issue of the obesogenic phenomena of increased lipid storage in adipose tissue (Shahnazaryan et al., 2019). Endocrine-disrupting chemicals are exogenous substances that are known to cause adverse health effects and changed in endocrine and hormone functioning (Trasande et al., 2015). The endocrine system plays a fundamental role in the regulation of the metabolism of fats, carbohydrates, and proteins for bodily energy. Any alteration from the hormones can lead to an imbalance in metabolism, and inappropriate deposits of fat, leading to obesity (Nasirullah, 2020).

Though experimental animal models confirm the effects of endocrine disruptors on adipose (fat cell) physiology and glucose metabolism, evidence is still somewhat confusing for human models due to conflicting results. Possible reasons for varying and inconsistent information regarding human models is conflicting data and results from different environments, which could include different social levels of individuals (Street et al., 2018). Another reason for data inconsistency is the limitation of methods that estimate and analyze the exposures within ecological levels and the variables that are associated with said levels (S. Lee et al., 2019). For example, risks and making choices are shown to be different between age groups; older adults (ages 40–60) are more prone to being aware of environmental hazards compared to their younger adult counterparts (ages 20–39; (Wee & Aris, 2019). Ecological variables apply to discovering obesogenic exposures. An extension of this notion is mentioned in Ruiz et al. (2018), that exposure to endocrine disrupting chemicals is higher among African Americans, Latinos, and low-income individuals, recognizing that there could be an uneven environmental exposure risk.

Based on the information provided, analogues to BPA (PBF and PBS) have a higher tendency to express obesogenic activity and functioning. However, many of the data are diminished when it comes to acrylamide and glycidamide exposure; there is a recognized threat to health, but more information needs to be provided to establish a causation. Speculation has been addressed in Equsquiza and Blumberg (2020), but there is no direct correlation as of yet.

Purpose of the Study

The purpose of the quantitative study was to investigate the impact of AA, GA, BPA, BPF and BPS on body mass index while adjusting for income, race, times ate fast food/pizza, food security, and the number of times an individual received health care within a year. This study was unique in how I addressed the possible health effects of GA, AA, BPA with the common analogs of BPS, and BPF; I assessed each chemical to determine if there were any changes in BMI through the intake of highly processed fast food.

Research Questions and Hypothesis

Research Question 1 (RQ1): What is the relationship among acrylamide, glycidamide, BPA, BPS, BPF and BMI while controlling for income?

Null Hypothesis ($H_0 1$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for income.

Alternative Hypothesis ($H_1 1$):There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for income.

Research Question 2 (RQ2): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the race?

Null Hypothesis ($H_0 2$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Alternative Hypothesis ($H_1 2$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Research Question 3 (RQ3): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza?

Null Hypothesis ($H_0 3$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Alternative Hypothesis ($H_0 3$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Research Question 4 (RQ4): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for food security?

Null Hypothesis ($H_0 4$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Alternative Hypothesis ($H_1 4$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Research Question 5 (RQ5): What is the relationship among, AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year?

Null Hypothesis (H_05): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Alternative Hypothesis (H_15): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Theoretical Foundation for the Study

I used the social-ecological model developed by McLeroy, Bibeau, Steckler, and Glanz (1988) and is as a variation for the Urie Bronfenbrenner ecological model as the theoretical framework for this study. The social-ecological model is a graphic depiction of the ecological theory of a specific health behavior or outcome. The social-ecological model is used to illustrate the health and well-being of an individual who is affected by multiple levels of influence (McLeroy et al., 1988). These influences happen on both the macro- and microlevel of environments. The microlevel involves an individual's physical and social environment, and the macrolevel consists of social norms, economic policies, and advertising (Cislaghi & Heise, 2018).

Urie Bronfenbrenner identified the social-ecological model as a conceptualization of understanding human development across multiple levels: individual, and family characteristics and characteristics of the home, community, and region (Kilanowski, 2017; McLeroy et al., 1988; Quick et al., 2017). The social-ecological model highlighted barriers that were key to prominent exposure throughout the levels of individual development and variables. Additionally, the data of the study produced a correlation with the chemicals and BMI that further solidifies the relationship with obesity. Each of the covariates served as stables for level of development. Each stage examined all levels of the social-ecological model and controlled for covariates, and the effects of BMI. The controlled covariates helped explained the impact the independent variables had of the sole dependent variable. The variables for each social-ecological model level are listed as such: income (intrapersonal), race/ethnicity (interpersonal), fast food and food security (organizational), and healthcare (community).

Additional insight to endocrine-disrupting chemicals concerning ultra-processed fast food and specific ecological levels can be pivotal in providing knowledge for the general public and the implementation of other policies to reduce the exposure of said chemicals to act as a top-down effect. The data established a positive correlation between specific endocrine disruptors and body mass index, ultimately providing a direct link to endocrine disrupting chemicals and obesity.

Nature of the Study

This was a correlational cross-sectional quantitative study. The design was consistent in understanding the possible relationship between specific endocrine-disrupting chemicals, fast food consumption, and obesity (as defined by the BMI rates). I aligned the study nature with the problem statement and purpose by determining whether or not the aforementioned chemicals had a positive association with obesity in various aspects of levels of influence. I analyzed environmental chemicals of BPA, BPF and BPS through the biomonitoring of urinary levels and their respective detection limits. AA and GA procedure measured the hemoglobin adducts in human whole blood or erythrocytes;

this laboratory method also utilized the limits of detection. I determined the aspects of influence by analyzing each social ecological level and their respective variable while determining if there was a difference in exposure to the identified endocrine disrupting chemicals at each level of the social ecological model (intrapersonal, interpersonal, organizational/institutional, and community levels).

Literature Search Strategy

I used the following keywords: *endocrine-disrupting chemicals, obesogens, obesogenic*, *obesity, NHANES*, *acrylamide, glycidamide, bisphenol A (BPA), bisphenol F (BPF), bisphenol S (BPS), processed food, ultra-processed food*, *fast food, oxidative stress, obesogenic mechanisms,* and *cardiovascular risk*. These keywords were found in the databases of Google, Google Scholar, Research Gate, Science Direct, and the National Center for Biotechnology Information (NCBI) at the National Institute of Health (NIH). The literature search pertained to peer-reviewed journal articles between the years of 2015–2020 to ensure that the information was still relevant to the subject.

Literature Review Related to Key Variables and/or Concepts

Darbre (2017) recognized that endocrine-disrupting chemicals have been shown to disrupt the actions of hormones. There have been increasing reports that emphasize how some endocrine-disrupting chemicals can interfere with the regulatory process in metabolism. The topic of endocrine disruptors has grown since the mid-2010s, and as such more quantitative journal articles have appeared in scientific and public health manuals. Endocrine disruptors can ultimately result in an imbalance in the regulation of body weight, which can lead to obesity. Due to their interaction with the human body and growing peer-reviewed articles, endocrine disrupting chemicals was the main point of this study. Specific endocrine disruptors are named and identified.

Adeyi and Babalola (2019) and Charisiadis et al. (2018), mentioned bisphenol A (BPA) as a synthetic organic compound that is known for its ability to interfere with the function of the endocrine systems. BPA belongs in Category 1 of endocrine-disrupting chemicals. Additionally, exposure to BPA can lead to obesity, thyroid dysfunction, and cardiovascular diseases. BPA is also widely used in food storage containers, feeding and nonreturnable bottles, food cans, and thermal papers. Regarding human exposure to BPA, food intake is considered to be the most serious and common of all the routes and can occur over long periods (Charisiadis et al., 2018). I analyzed the relationship between BPA, fast food, and food security category since these variables were related to the subject matter in question. I determined that the exposure from BPA is significant in impacting obesity by any means throughout the social levels in an individual's environment.

Andújar et al. (2019) emphasized how BPA is known for causing adverse health effects, and analogs of BPA (BPF and BPS) have been used to counteract the high exposure to BPA. However, because of their similar chemical structures, BPS and BPF tend to cause similar health effects, including obesity (Apau et al., 2018). Jacobson et al. (2019) suggested that BPA and its analogs are correlated with obesity. I interpreted this as significant since Jacobson et al. (2019) used the NHANES and quantitative methodologies to determine their result. I analyzed BPF and BPS in this study as well. I found that most items classified as BPA free may have opted to use either analogue as a substitute. Since both analogues had the potential to cause similar health effects like BPA, I included BPF and BPS in my research.

Higher exposure to BPS may be associated with greater BMI and waist circumference. Urinary BPA and BPS were strongly correlated with oxidative stress, which is one of the molecular mechanisms involved in the development of obesity-related complications (Lechuga-Sancho et al., 2018; Liu et al., 2017). BPF and BPS, similar to BPA, are endocrine-disrupting chemicals and display a disruption in hormonal activity. Both affect the signaling pathways involved in lipid metabolism and adipogenesis. BPS and BPF, the substitutes for BPA, are associated with general and abdominal obesity (Liu et al., 2017, 2019).

AA is a chemical that is widely used in the manufacturing of paper, dye, and various industrial products; it is also formed unintentionally as a byproduct of cooking carbohydrate-rich foods at high temperatures by frying, baking, and roasting (Egusquiza & Blumberg, 2020). Both AA and GA are found in ultra-processed foods and are characterized by their lower nutritional quality and presence of additives. Ultra-processed food intake is associated with higher risks of obesity (Fiolet et al., 2018). Packaging of ultra-processed foods may contain some materials that resemble carcinogenic and obesogenic properties. Ultra-processed food intake may elevate the role of cause mortality by increasing exposure to contaminants and environmental chemicals (H. Kim et al., 2019). The ingestion of ultra-processed food is known to increase the exposure to obesogenic chemicals. The identification of AA and GA as endocrine disrupting chemicals continues to be a new one. However, because they have the potential to be damaging to human health through everyday means, both will be involved in the study. Since the identification of AA and GA is still complicated, the results may or may not be limited. Lastly, I found that Equsquiza and Blumberg (2020) emphasized that multiple environmental factors can impact obesity susceptibility, this could include factors that contribute to the social-ecological model.

Most fast food contains a large amount of sugar, fats, carbs, and very few minerals and vitamins, meaning that people are taking in large quantities of calories, which often leads to weight gain and obesity if not managed (Nasirullah, 2020). I concurred with Santos et al. (2014), as mentioned in Nasirullah (2020), that several products act as obesogens, including sweets and sugar-based dishes, pastries, fast food, oils, milk, cereals, cakes, and sauces. Fast-food consumption has been a potential risk factor for obesity (Nasirullah, 2020). This raises the question of what is being put into our bodies in terms of various chemical compounds. The results of the study infer that food items are not being investigated thoroughly for endocrine disruption. To compensate for this, food security and the amount of times an individual has ingested fast food were readily used for data analysis. Additionally, because fast foods are inexpensive, as stated by Ruiz et al. (2018), the variable of income was inspected accordingly. For this reason, race was identified as an appropriate variable as well; fast food ingestion can be different among races. Race and income, more often than not, are significant demographic variables in studies, both were sufficient in identifying levels of exposure in my theoretical framework.

Bisphenol A

There is a growing concern about the adverse effects of endocrine disrupting chemicals. BPA, which is an estrogenic and obesogenic compound, is used in the plastic and medical industry and has a dominant position among endocrine disrupting chemicals. Due to its omnipresence across the biosphere, populations of all age groups and health statuses are unavoidably exposed to BPA (Dabeer et al., 2020). BPA is harmful to human health with transgenerational exposure as a consequence (Dabeer et al., 2020). Regardless of the admission of harmful effects of BPA, there is no report and little to no research on the transgenerational effects of BPA on persons with metabolic disorders, particularly obesity (Dabeer et al., 2020).

Although BPA has been largely studied as an obesogenic agent, it is speculated that BPA might contribute to weight gain, insulin resistance and pancreatic β-cell dysfunction in pregnancy, potentially playing a role in pregnancy complications, such as gestational diabetes mellitus. The prevalence of obesity has indeed risen over the past few decades, and it is possible that interactions between multiple environmental factors and genetic factors might explain this health trend (Filardi et al., 2020).

Bisphenol S

Though bisphenol analogues of F and S have come to replace BPA in some regards, little to no research was done to analyze the safety of BPA products when BPF and BPS are used instead. Because BPS is in the most common substitute for BPA, it will be in the public’s best interest to analyze BPS and add regulations, if necessary, especially since BPS has become so normalized and common in society (Thoene et al., 2020). Additionally, there have been conflicting articles that demonstrate how BPS was described as the least toxic analogue when compared to BPA and BPF. Regardless of this, speculation with bisphenols and metabolic disorders (diabetes, cancer, etc.) continue, but not much information is provided relating to obesity.

BPS is used in a variety of consumer products such as the manufacturing of polycarbonates, epoxy resins, and most commonly thermal papers and dye developers (Thoene et al., 2020). BPS is known for being an endocrine disruptor that mimics normal hormonal activity, which leads to adverse health effects. However, there is no definitive relationship or correlation with obesity; it has yet to be established (Thoene et al., 2020).

Bisphenol F

Bisphenol F is considered an aromatic organic compound that is widely used in industrial and household products such as plastics, pipes, dental sealants and food packaging (Ijaz et al., 2020). BPF is also a known endocrine disruptor found in drinking water that is transferred through pipes (Ijaz et al., 2020). BPF is also found in fruits, vegetables, meat, beverages, candies and tin cans (Ijaz et al., 2020).

BPS and BFF initially did not have an association linked to obesity in a cross-sectional study of adults after adjusting for their lifestyles and socioeconomic factors (Liu et al., 2017). However, recent studies have revealed that BPS and BPF were associated with obesity in children (Basak et al., 2020). Studies contradict each other and there is no association of obesity and BPF and BPS among persons classified as adults (Liu et al., 2019). Additional examinations need to be done to determine if substituting BPA for analogues is an effective strategy (Egusquiza & Blumberg, 2020).

Definitions

Adult Population. The adult population will be defined as people who are 18 years and older (adapted from the NHANES website 2020). The population consists of both male and females. The population samples noninstitutionalized U.S. citizens in all 50 states and Washington D.C. The survey examines a nationally representative sample of about 5,000 persons (Centers for Disease Control and Prevention, 2018).

Body Mass Index (BMI). BMI is a person's weight in kilograms divided by the square of height in meters. High BMI is an indicator of high body fatness and is often used as a screening tool. Traditional BMI categories are as such: (a) underweight if less than 18.5, (b) normal if between 18.5 and < 25.0, (c) overweight if between 25.0 and < 30, and (d) obese if 30.0 or higher. Should the BMI be over 30.0, obesity will be divided into subcategories: Class 1: BMI of 30 to < 35, Class 2: 35 to < 40, and Class 3: 40 or higher; Class 3 should be classified as 'extreme' or 'severe' obesity (Centers for Disease Control and Prevention, 2020b).

Endocrine disrupting chemicals (EDCs): These chemicals are defined as any substance that interferes with normal hormonal activity. The category of EDCs can include metals, industrial chemicals, pesticides, fungicides, herbicides, pharmaceutical drugs, personal care products, toys, cosmetics, food/packaging, and natural and synthetic hormones (Zlatnik, 2016). These chemicals produce adverse developmental, reproductive, neurological, and immunological effects in mammals (Yang et al., 2015).

Food Security. Food insecurity, as defined by the U.S. Department of Agriculture, is having inconsistent access to adequate food due to limited financial resources and other factors (Pruitt et al., 2016). Adult food security was divided into four categories: 1 (Adult full food security; no affirmative response), 2 (Adult marginal food security; 1–2 affirmative responses), 3 (Adult low food security; 3–5 affirmative responses), and 4 (Adult very low food security; 6–10 affirmative responses). For households without children under the age of 18, their household food security category (FSDHH) will be identical to their adult food security category (FSDAD; adapted from NHANES website 2020).

Gender. Gender will be defined as one of two types: male and female (Centers for Disease Control and Prevention, 2018).

Income (Annual Household Income). This variable will indicate the total annual family income or annual individual income (for households with one person or households comprised of unrelated individuals) (Centers for Disease Control and Prevention, 2017a). The income will be reported as a range value in dollars. This is a continuous scale variable.

Obesogens. The terms obesogens and EDCs are often used interchangeably. Obesogens are endocrine disruptors that induce obesity (Heindel et al., 2017). Obesogens are known for targeting gene networks that function to control intracellular lipid homeostasis, and the proliferation and differentiation of adipocytes (adipose tissue cells or fat cells; Yang et al., 2015). Obesogens are defined as a subset of endocrine disrupting chemicals (Griffin et al., 2020).

Peroxisome Proliferator-Activated Receptors γ (PPARγ). One of the major group of regulators that is targeted by obesogenic chemicals; it is a nuclear hormone receptor (Yang et al., 2015).

Race. Subgroups that will be mentioned in the NHANES data are Mexican American, Other Hispanic, Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Asian, and other race-including multi-cultural (Centers for Disease Control and Prevention, 2020b).

Assumptions

The NHANES interview includes demographic, dietary, socioeconomic, and health related questions. The NHANES survey was unique in that it combined interviews and physical examinations. Since the NHANES survey utilized health interviews, I was assumed that the participants were honest during the data collection process. I also assumed that anonymity and confidentiality was be assured during the course of the NHANES; because of this, the possibility of respondents providing untruthful answers were very slim.

Additionally, I assumed that all participants understood the directions of the administrators and complied correctly to ensure the accuracy of the survey. The assumptions were necessary to state in this context as it is impossible to determine wither or not respondents truthfully provided information and wholeheartedly understood the directions of the survey.

Scope and Delimitations

The scope of this study was limited in determining if there was a concrete association or correlation with obesity as measured by BMI and specific endocrine disrupting chemicals of BPA, BPF, BPS, AA and GA with the analysis of age and race as possible exacerbation of the chronic disease. A detailed analysis and closer inspection of the aforementioned variables will be helpful in providing additional insight as to which variables, if applicable, positively contribute to obesity, which in turn should improve the understanding of endocrine disruptors that identify as obesogens.

In quantitative studies, there will always be the possibility that some unknown variable, or confounding variable, that may explain the relationship between the predictor variables and the outcome. To reduce the possibility of internal validity, demographic variables were included to analyze within this study.

The study population was comprised of individuals who live in the United States population. For external validity, since representative sampling was used in the NHANES, the result of the analysis will be generalized to the U.S. adult population, thus accepting the small percentage of individuals that will be excluded from the population initially stated by the NHANES.

Significance, Summary, and Conclusions

This study expanded the understanding of attitudes that may contribute to exposure to the subset of endocrine disrupting chemicals, known as obesogens. Additionally, the study determined which chemicals may have a higher tendency to engage the inflammation and adipogenesis of fat cells which adheres to the inference or activation of PPARγ (Griffin et al., 2020).

Though some chemicals have been identified as definitive endocrine disruptors, more research will be needed to account for other endocrine disruptors that have a tendency to display obesogenic characteristics. There is considerable evidence that leads to the determination that BPA can lead to adverse health problems. Unfortunately, the producing of BPA-free items has introduced the notion to utilize analogues of BPA, namely, BPS and BPF (Wang et al., 2019). Further developments have suggested that the analogues are just as toxic to health, therefore the substitution of other bisphenols for BPA may not be an effective and health safe strategy for limiting the exposure to endocrine disruptors (Egusquiza & Blumberg, 2020; Lehmler et al., 2018). With this study, it is hoped that further advancement and awareness of BPA and its analogues will continue to spread within the scientific community, as well as the political arena in efforts to build a platform on how said chemicals are indeed harmful to the development physiology of humans pertaining to obesity.

The same can be said for the chemicals of AA and GA. Until recently, both acrylamide and glycidamide have not been researched extensively in terms of relation to obesity or fat accumulation. Recent developments have postulated that AA and to some extent GA might be an obesogenic agent. According to Lee and Pyo (2019), as mentioned in Egusquiza and Blumberg (2020), acrylamide is formed as an unintentional byproduct of cooking carbohydrate-containing foods at high temperatures via baking, roasting, and frying which is suspected to be the main source of human exposure. Furthermore, there has not been a solidified relationship between acrylamide and obesity. However, one analysis of the NHANES data from 2003-2006 from Huang, Zhuang, Jiao, Wang, and Zhang (2018) demonstrated a positive association between GA and obesity, although both AA and GA were proposed as biomarkers of AA exposure in humans. Due to frequent inconsistencies, more data is needed to establish whether both AA exposure is associated with obesity (Huang et al., 2018).

The general goal of the study was to determine whether or not specific endocrine disrupting chemicals with possible obesogenic tendencies have a positive association with obesity. Should this study be successful with proving a relationship, this could provide additional information in categorizing obesogens and identifying other variables that contribute to the public health issue of obesity.

Section 2: Research Design and Data Collection

Introduction

The purpose of the study was to analyze and determine if there is a relationship between the specific endocrine disrupting chemicals of BPA, BPF, BPS, AA, and GA with BMI with the controlled variables of fast food/pizza, race/ethnicity, income, access to health care, and food security. The purpose of the study was to gain further understanding on a new yet grey area of obesity research. Said research will help in the implementation of strategies to combat this chronic illness. Additionally, this study provided some insight on factors that contribute to endocrine disrupting chemicals and obesogen exposure, hence as to why the demographic factors of race, income, food security, number of meals prepared at fast food restaurants, and number of times received health care were examined as confounding variables.

By examining specific chemicals, my study could fill the gap in literature that relates to demographic variables, and the reactivity of AA and GA as identifiable obesogenic chemicals. The findings of this study could be used to develop policies appropriate in limiting exposure and providing alternative solutions to the use of chemicals in environmental, personal care products, food, and food storage. This chapter will address the research design, methodology, the data analysis plan, possible threats to validity, and ethical procedures.

Research Design and Rationale

The independent variables, which is the exposure variable, included the endocrine disrupting chemicals of BPA, BPF, BPS, AA and GA. These are the chemicals to have suspected obesogenic properties. The dependent variable, which is the outcome, consisted of obesity, as it is measured by BMI. The confounding variables, the variables that can affect both the independent and dependent variables, were the demographic variables. Said variables included income, race, food security, the number of times received healthcare, and the number of meals from pizza and fast-food restaurants.

My research design is a cross-sectional design. Cross-sectional designs with correlational tendencies are typically used to examine if changes in variables will be related to changes in more variables (Lau & Kuziemsky, 2017). Correlational cross-sectional studies are a type of cohort study where one comparison is made between exposed and unexposed subjects. The cross-sectional aspect addressed the relationship between diseases, other health related characteristics, and other variables of interest that exist within the population and exposure and outcomes were measured at the same time (Lau & Kuziemsky, 2017). This is best for quantifying a disease and risk factor, the risk factor being specific endocrine disrupting chemicals.

The research design was appropriate for the research questions because both focus on levels of influence that affect the individual. The research questions themselves were inclusive of all factors, at least in this situation, that aimed to determine if the health behavior of exposure to endocrine disputing chemicals was in tandem with BMI levels. The research questions utilized levels of interdependence between people, their behavior, and their social and physical environments (Essiet et al., 2017). The social-ecological is an ideal framework for understanding the importance and impediments that enablers have relating to obesity. The model addresses details toward the interpersonal, intrapersonal, organizational and community factors, which have the capability to expedite exposure to obesogenic chemicals.

There were no issues with time and expense since cross-sectional studies are usually conducted at a relatively fast and inexpensive pace. Furthermore, the cross-sectional study design is ideal in public health planning, monitoring, and evaluation of issues pertaining to the field, hence endocrine disruptors. Cross-sectional studies provide public health leaders and scientists information about the prevalence of outcomes or exposures (Setia, 2016). By monitoring outcomes and exposures in the study participants at the same time using the NHANES, this study provided some insight on exposures to endocrine disruptors throughout several levels of influence and how said exposure effects BMI levels, thus establishing either a positive relationship with obesity and endocrine disruptors.

Methodology

Population

The sample for the survey was selected to represent the United States population of all ages and races; to produce reliable statistics, the NHANES used an oversample of persons 60 and older, since the United States had experienced a rapid growth in the number of older Americans (Centers for Disease Control and Prevention, 2020b).

In the cycle year of 2015–2016, 15,327 persons were selected for the NHANES from 30 different survey locations. Of those selected, 9,971 completed the interviews and 9,544 were examined (Centers for Disease Control and Prevention, 2020b). The oversampled groups in 2015–2016 were: Hispanic persons, non-Hispanic Black persons, non-Hispanic Asian persons, non-Hispanic White persons and other persons below the 185% of the Department of Health and Human Services poverty guidelines, and lastly non-Hispanic White persons and other persons aged 80 years of age and older (Centers for Disease Control and Prevention, 2020b).

Sampling and Sampling Procedures

The NHANES addresses multistage probability design to sample the civilian population that resides in all 50 states and Washington D.C. The following stages were conducted in this order: (a) the selection of primary sample units (PSUs) (counties, groups of tracts within counties, or combinations of adjacent counties), which are defined as countries or small groups of contiguous counties, (b) the selection of segments within PSUs that constitute a block or group of blocks containing a cluster of households, (c) the selection of specific households within segments, and (d) the selection of individuals within a household (Centers for Disease Control and Prevention, 2018). The oversized subgroups of race and Hispanic origin created the sample design. Eligibility for inclusion within the survey determined through sampling from Race and Hispanic census information (Chen et al., 2020).

The race and Hispanic origin variables were based on survey response. In addition, the race and Hispanic origin variable within the NHANES indicates only single race categories for non-Hispanic White, Black, and Asian groups, with participants reporting belonging to other or multi-race groups coded into the ‘other races, including multiracial’ category (Chen et al., 2020).

It should also be noted that in previous NHANES cycles, the low-income threshold for oversampling non-Hispanic White and other persons was initially set at 130% of the federal poverty line, which coincidently is the threshold used to determine income eligibility for the Supplemental Nutrition Assistance Program (SNAP, aka the Food Stamp Program). The oversampling threshold was changed to 185% of the federal poverty level with the NHANES cycles of 2015–2018; the 185% threshold is used for determining income eligibility for the Supplemental Nutritional Program for Women, Infants, and Children (WIC; (Chen et al., 2020).

Data Access

The datasets of the NHANES 2015–2016 cycle identified as public-use data. Public-use data files provided full access to view and understand the full scope of the data (Centers for Disease Control and Prevention, 2018).

Power Analysis

To obtain the results of a power analysis, I utilized G*Power. A linear multiple regression analysis was the best option. The linear multiple regression analysis is appropriate for various research designs that have the goal of assessing the predictive value of independent variables on the one dependent variable while controlling for other variables, or confounding variable (covariates).

In order to examine the research questions, a multiple linear regression assessed if the independent variables, which included confounding variables (covariates) could predict the dependent variable of BMI. The data analysis plan proceeded after the descriptive statistics.

The power and effect size was calculated by using linear multiple regression analysis, otherwise defined as an F-test in G*Power. Given the number of predictors, which included independent variables and covariates (10), with the standard power or beta (β) of 80% (.80), an effect size (f^2) of 0.15, and an alpha (α) of 0.05, or 95%, the sample size was 118 and the actual power being 80%. The statistical power of the study depends upon the effect size and sample size. The lower an effect size, the more subjects will be needed to have adequate power to decide that 'no difference' is an option and a true finding (Sullivan, 2012). Because no other study about this topic clearly stated an effect size being used, the medium effect size (f^2) of 0.15 (Cohen, 1988) was used for the estimation of the needed a sample size of 118 participants for this study.

Justification for Effect Size

The sample size from the G*Power program had a medium effect size of 0.15 while using an alpha of 0.05 and a power reading of 80%. The effect size of 0.15 was considered medium by Cohen's (1988) measure of the effect size in multiple regression (Faul et al., 2009; PASS Sample Size Software, n.d.). The linear multiple regression: fixed model R^2 deviation from zero provided a power analysis for omnibus F-tests of the null hypothesis that squared multiple correlation between a criterion value of Y (the dependent variable) and several predictor variables, which can include the independent variables and covariates, acting as controlling variables (Faul et al., 2009). The null hypothesis equaling zero (0) versus the alternative hypothesis that is larger and different from zero:

$$H_0: \rho^2 y, x1 \ldots x_m = 0$$

$$H_1: \rho^2 y, x1 \ldots x_m > 0$$

Aloe & Becker (2012) stated that the effect size represented the predictive power of the independent variables and covariates form a multiple regression model, when there was a semi partial correlation of the predictors with the outcome interest. Therefore, I deemed thee effect size fitting since linear multiple regression is correlational procedure that looks at the relationships between predictor variables and the criterion variable (dependent). Furthermore, Olmos (2012) mentioned how the effect size helps the readers understand the magnitude of differences found; it is generally accepted that effect sizes facilitate a decision regarding the presence of a clinically relevant information. With this in mind, the effect size remained at the average value of 0.15.

Instrumental and Operationalization of Constructs

Published Instruments

The National Center for Health Statistics conducted and developed the NHANES. It was designed in order to assess the health and nutritional status of adults and children within the United States, and to eventually track any changes over time. The National Center for Health Statistics is responsible for protecting the confidentiality of all survey respondents, including the NHANES respondents (Patel et al., 2016). Because the NHANES 2015–2016 data successfully monitored demographic variables along with environmental exposures that have been measured and categorized, the data are deemed appropriate for the use of this study. Additionally, data from the NHANES 2015–2016 cycle were the most recent NHANES data that is in its entirety. The 2015–2016 cycle was ideal for analyzing and examining environmental endocrine disruptors within the United States among ample participants.

Developer Permission

The data for this study were readily accessible on the Centers for Disease Control and Prevention website. Each dataset was downloaded and accessed through IBM SPSS version 25. No permission needed; the data were openly available to the general population and the cycle year was in its entirety.

Reliability and Validity

Validity refers to the degree to which a study can accurately assess the specific concept that the researcher is attempting to measure. Reliability is the focused on the accuracy of the measuring instrument, in this case the NHANES, which relates to validity; in this study, I deduced that validity was a concern for measuring.

For this particular study, I took several steps to ensure the validity and reliability of the study. (Pirkle (2019b) mentioned how validity for bisphenols included the checking of all sample and analytical data after being entered into the NHANES database for transcription errors. However, because my saved data from the NHANES 2015–2016 cycles acted as the secondary data, all information labeled by the appropriate cycle year was made accessible to IBM SPSS. AA and GA data had the same process.

As the NHANES was being conducted, there were numerous steps to ensure the validity of the data collected: (a) laboratory staff had to undergo certification process in laboratory science, (b) for each method used in the survey, there was clear instruction in the NHANES laboratory/medical technologies procedures manual on proper collecting, labeling, preserving, and processing samples, and (c) laboratory results were entered directly into the NHANES system, high and low values were evaluated for a second time by NCHS staff with various consistency checks (Centers for Disease Control and Prevention, 2020a).

In scientific articles and briefs, the quality and validity of biomarkers was recognized. Quality and validity of biomarkers often include biological factors that would need to be considered, including age, sex, race/ethnicity, smoking, fasting status, pregnancy, and obesity (Pfeiffer et al., 2017). Other factors included impaired renal function (plasma total homocysteine and serum methylmalonic acid). The Centers for Medicare and Medicaid Services regulate all laboratory testing (excluding research) performance in human subjects in the United States through the Clinical Laboratory Improvement Amendments (CLIA) laboratories. Scientists dealt with biological specimens for providing information regarding diagnosis, treatment, prevention, and the assessment human health. All laboratories and scientists were CLIA certified; the NHANES required the use of CLIA laboratories for the results regarding NHANES participants (Pfeiffer et al., 2017). Laboratory requirements for CLIA include personnel standards, patient treatment, test management, quality assurance, proficiency testing, inspection and enforcement.

Laboratory Quality of AA and GA

Washed-packed red blood cell specimens were processed, stored, and shipped to the Division of Laboratory Sciences, National Center for Environmental Health, and the Centers for Disease Control and Prevention for analysis in Atlanta, Georgia. Vials of specimens were stored under appropriate frozen conditions of -30°C until they were shipped to the National Center for Environmental Health for testing (Pirkle, 2019b).

Laboratory Quality of BPA, BPF, and BPS

Urine specimens were processed, stored, and shipped to the Division of Laboratory Sciences, National Center for Environmental Health, and the Centers for Disease Control and Prevention for analysis in Atlanta, Georgia. Urinary vials were stored under appropriate frozen conditions of 20°C until they were shipped to the National Center for Environmental Health for testing (Pirkle, 2019a).

Operationalization

Definitions of Variables

Acrylamide (AA)

According to the NHANES codebook, AA is identified as a neurotoxic, mutagenic to animals and humans. People are exposed to acrylamide through occupational activities (wastewater treatment, paper and textile industry, dye manufacturing), tobacco smoke and dry heated food. However, actual exposure of AA and possible changes are not identified. AA has a lower limit of detection at 3.90 picomoles over per gram of hemoglobin (pmol/g Hb). Originally, AA was coded as a continuous variable; however, the creation of dummy variables transformed AA into a dichotomous variable. The value of 1 equating to the lower limit of detection (LLOD) (3.90) through the highest value, and everything else being coded as 0.

Adult Food Security Category (Food Security)

Food security pertains to the households without children under the age of 18. Food security is defined by Gibson (2020) as the basic means to regularly have enough food to eat, not merely for the next day, but to have a plentiful supply for months and even one year. Food security was a categorical nominal variable with the following groups: 1 = adult full food security (no affirmative response); 2 = adult marginal food security (1-2 affirmative responses); 3 = adult low food security (3-5 affirmative responses); and 4 = adult very low food security (6-10 affirmative responses).

Bisphenol A (BPA)

BPA is an environmental chemical that is used in the manufacturing of resins and plastics for the use of food containers as protective coatings. BPA was measured as nanograms per milliliter (ng/mL), which is used during urine analysis. BPA in its original form was a continuous metric variable in the NHANES but was recoded as dichotomous (with dummy variables) based on the LLOD for BPA, which was 0.2. 1 pertaining to the values of 0.2 and beyond, and 0 for all other values.

Bisphenol F (BPF)

BPF is seen as an alternative to BPA. It has been introduced to the public in efforts to replace BPA. Because BPF was produced through urine analysis, it was measured as ng/mL. BPF was recoded as a dichotomous variable, with choices of 1 and 0; 1 being the LLOD of 0.2 and beyond, 0 had all other values.

Bisphenol S (BPS)

BPS was seen as another alternative for BPA. Like BPF, BPS was introduced to the public in an attempt to reduce the exposure of BPA and eventually replace the compound with other options. BPS was measured exactly like BPA and BPF, through urine analysis as ng/mL. BPS was recoded as a dichotomous variable, with choices of 1 and 0; 1 being the LLOD of 0.1 and beyond, 0 had all other values.

Body mass index (BMI)

BMI was calculated as weight in kilograms divided by height in meters squared and rounded up to one decimal point (kg/m^2). It was assumed that the BMI variable was exclusive for adults since there was a separate variable for children and adolescent BMI. BMI was measured as a metric or continuous variable.

Frequency of Meals from Fast Food/Pizza (Fast Food)

Respondents were asked how many times they had received meals from fast food and pizza places in the past seven days. If the frequency was recorded as never, the value was coded as 0. If the frequency was reported as more than 21, the value was coded as 5555. Frequency of meals was a categorical nominal variable.

Glycidamide (GA)

GA is defined as the primary metabolite of AA and has a higher reactivity towards nucleophilic reagents. The GA lower limit of detection is measured as pmol/g Hb. Like AA, GA was originally a continuous variable, but was altered to have the coded values of 1 and 0 or dummy variables. 1 equating to GA LLOD of 4.90 and onward and zero coded for all other values.

Income

Income indicates the total annual household income amount in United States dollar ranges. During the household interview, the respondent was to report total income for household or individual in the last calendar year in dollars. The dollar amount was coded into range values; income was a categorical nominal variable. The range values were as follows:

$0 to $4,999; $5,000 to $9,999; $10,000 to 14,999; $15,000 to 19,999; $20,000 to $24,999; $25,000 to $34,999; $35,000 to $44,999; $45,000 to $54,999; $55,000 to $64,999; $65,000 to $74,999; $75,000 to $99,999; $100,000 and over; $20,000 and over; and under $20,000 (Centers for Disease Control and Prevention, 2017a).

Race/Ethnicity (Race)

The categorical variable of race will be derived from responses to the survey questions regarding race and ethnicity (Hispanic) origin. In addition, the race variable was meant to accommodate the oversampling of subgroups in the 2015-2016 survey cycle. Subgroups include Mexican Americans, Other Hispanic, Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Asian, and other Race including Multi-Racial (Centers for Disease Control and Prevention, 2017a).

Times received healthcare in past year (Healthcare)

The hospital utilization and access to care questionnaire provided respondent level interview data on self-reported health status and access to care. The questionnaire was asked in respondent homes by trained interviewers using the computer assisted personal interview system. The question was phrased: “How many times has [the respondent] seen a doctor or other health care professional about [their] health at a doctor's office, a clinic or some other place? Do not include times [they] were hospitalized overnight, visits to hospital emergency rooms, home visits or telephone calls"(Centers for Disease Control and Prevention, 2017b). This variable was a categorical nominal variable by nature.

Study Variables and Covariates

This study examined the association among urinary bisphenols (A, F, S), the hemoglobin adducts of AA, GA and other variables that pertained to each level of the socio-ecological model (i.e. race, income, intake of pizza/fast food, food security, and the number of times received health care), and the dependent variable of BMI for a total of 11 variables.

Demographic data (DEMO_I) consisted of race (RIDRETH3), and income (INDHHIN2). Body mass index (BMXBMI) was located in the body measures data (BMX_I); food security (FSDAD) was in the food security section; the number of times received health care over the year (HUQ051) was located in hospital utilization and access (HUQ_I); the number of meals from fast food/pizza (DBD900) was in the diet behavior and nutrition (DBQ_I) dataset; the urinary BPA (URXBPH), BPF (URXBPF) and BPS (URXBPS) were in the dataset titled personal care and consumer product chemicals (EPHPP_I); and lastly the acrylamide (LBXACR) and glycidamide (LBXGLY) variables were found in the acrylamide and glycidamide (AMDGLD_I) dataset. Detection limits for the BPA, BPF and BPS were 0.2, 0.2, and 0.1 ng/mL respectively. Detection limit for acrylamide was 3.90 pmol/g Hb; glycidamide had a detection limit of 4.90 pmol/g Hb. A table listing the dependent variable, independent variables and covariates are explained below.

Study Variables and Covariates

Table 1

Study Variables and Covariates

Variable Type	Variable Name	Codebook Name	Level of Measurement
Dependent	BMI	BMXBMI	Continuous
Independent	BPA	URXBPH	Dichotomous
Independent	BPF	URXBPF	Dichotomous
Independent	BPS	URXBPS	Dichotomous
Independent	Acrylamide	LBXACR	Dichotomous
Independent	Glycidamide	LBXGLY	Dichotomous
Covariate	Race	RIDRETH3	Categorical
Covariate	Income	INDHHIN2	Categorical
Covariate	Food Security	FSDAD	Categorical
Covariate	# meals fast food/pizza	DBD900	Categorical
Covariate	# healthcare over year	HUQ051	Categorical

Table 2

Descriptive Statistics

	N	Min.	Max.	Mean	Std. Dev.
AA	9971	.00	1.00	.2420	.42832
GA	9971	.00	1.00	.2274	.41915
BPA	9971	.00	1.00	.2520	.43420
BPS	9971	.00	1.00	.2399	.42704
BPF	9971	.00	1.00	.1165	.32089
Race	9971	1	7	3.21	1.680
Fast Food	7213	.00	5555.00	3.4861	92.49148
Healthcare	9941	.00	8.00	2.3062	1.87066
Food Security	9629	1.00	4.00	1.7603	1.04752
Income	9272	1.00	15.00	8.7046	4.39280
BMI	8756	11.50	67.30	26.0167	7.96387
Valid N	5935				

Data Analysis Plan

As stated previously, the data used for this study was obtained from the Centers for Disease Control and Prevention website. The NHANES 2015-2016-year cycle data was obtained from the website in its initial SAS format. Fortunately, the SAS data was able to be opened in the IBM SPSS version 25 for macOS Mojave. Descriptive statistics was conducted to discover the minimum and maximum scores of each variable to determine whether there will be any values that could be defined as outliers or values that lie outside of the expected range. If abnormal values were found, those values were recorded as missing before the conducting of any statistical analysis or procedure.

Research Questions and Hypothesis

Research Question 1 (RQ1): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for income?

Null Hypothesis ($H_0$1): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for income.

Alternative Hypothesis ($H_1$1): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for income.

Research Question 2 (RQ2): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the race?

Null Hypothesis ($\mathrm{H}_0$2): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Alternative Hypothesis ($\mathrm{H}_1$2): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Research Question 3 (RQ3): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza?

Null Hypothesis ($\mathrm{H}_0$3): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Alternative Hypothesis ($\mathrm{H}_0$3): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Research Question 4 (RQ4): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for food security?

Null Hypothesis ($H_0$4): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Alternative Hypothesis ($H_1$4): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Research Question 5 (RQ5): What is the relationship among, AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year?

Null Hypothesis ($H_0$5): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Alternative Hypothesis ($H_1$5): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Statistical Test

Linear Multiple Regression (LMR) analysis, also known as multiple linear regression, will be use used to assess if the independent variables could predict the dependent or criterion variable; this process will be for each research question. The standard method enters independent (predictor) variables simultaneously into the model; variables were evaluated by what they add to the prediction of the dependent variable, which differs from the predictability of other predictor variables (Moran, 2013). Covariates were added to the linear multiple regression due to how covariates can correlate with either or both the dependent and independent variables (Allen, 2017). The covariates in this instance were demographic factors for the most part, which include income, race, food security, access to health care, and intake of fast food/pizza.

In LMR, the *f*-test was used to assess whether the set of independent variables predict the dependent variable. *R* squared (R^2 or the multiple correlation coefficient) was reported and used to determine how much variance in the dependent variable can be accounted for by the independent variables and covariates; the t-test determined significance of each predictor and beta coefficient to determine the extent of the prediction for each independent variable (Moran, 2013).

LMR is a parametric test with specific assumptions (e.g., linear relationship, normality, no or little multicollinearity, homoscedasticity, etc.). In Section 3 regression diagnostics were performed and if those assumptions were not met, binomial logistic regression would have been used by recoding the outcome variable (BMI) into a binary categorical variable (e.g., high vs. low BMI).

Threats to Validity

Threats to External Validity

External validity, as defined by Lewkowicz (2001) from Andrade (2018), examines whether the findings of a study can be generalized, or be made into broad statements within other contexts; in short, external validity extends to the application of findings to other people and settings. One particular threat to external validity that could have affect the study was selection bias.

Selection bias arises when the observed population are not being represented; when a population is not properly represented, the phenomenon can lead to an increase in external validity (Andrade, 2018; Haneuse, 2016). A lack of representations would be a major gap, specifically in determining whether or not the results based on a sub sample of respondents are generalizable. Selection bias had already been addressed in the NHANES dataset; the NHANES dataset, which was developed by the National Center for Health Statistics already identified subgroups of the population. It was already established that the NHANES conducted oversampling of the Non-Hispanic Asian population, in addition to the oversampling of Hispanics, Non-Hispanic Blacks, older adults (age 80 and older), and lower income Non-Hispanic Whites who were at or below the 185% poverty guidelines (Centers for Disease Control and Prevention, 2020b).

Threats to Internal Validity

Internal validity, as defined by Slack and Draugalis (2001), is the degree of control within the study design. In other words, it is the degree to which changes in the dependent variable can be attributed to the independent variables (Thompson & Panacek, 2007). One major threat to internal validity was confounding bias.

Confounding bias is arguably one of the more common threats to internal validity (Slack & Draugalis, 2001). Confounding bias usually appears when factors that affect both treatment and outcome are not properly controlled. When more than one thing is different on average between the groups being compared, confounding can be a pivotal threat (Matthay & Glymour, 2020; Seltman, 2018). Confounding variables are one common source of bias that can influence study outcomes even though the variable in question may or may not have a primary focus on the study (Zheng & Dirlam, 2016). Confounding, sometimes extraneous, variables can be an unrecognized cause of the study results. Throughout a majority of the time, confounding bias can be resolved with randomization and restriction. Randomization is described as the best way to assure that all potential confounding variables are equal on average among treatment groups. Additionally, adjustment can help in the issue of confounding; adjustment can include the measuring of confounder variables while in the process of data gathering (Pourhoseingholi et al., 2012). In the case of this study, adjusting will be used to combat confounding. Confounding will be limited with the inclusion of comparing the results of simple regression (no confounder) and multiple linear regressions. This will be able to clarify how much the confounders in the model distort the relationship between the exposure to endocrine disruptors and the outcome of BMI (Pourhoseingholi et al., 2012). If the regression coefficient from the simple linear regression model changed by more than 10%, then there was a significant confounding variable (Boston University School of Public Health, 2013).

Threats to Construct Validity

Construct validity, as defined by Seltman (2018), is a characteristic of devised measurements that describes how well the measurement can stand in for the scientific concepts that are the prime targets of the scientific learning and inquiry. Once variable definitions are set and classified, construct validity makes sure that the measure will correlate with other measures to determine if it is a good concept of interest (Matthay & Glymour, 2020). One possible threat to construct validity is inadequate explication of constructs, which is when there is a failure to explicate a construct; in turn this may lead to incorrect ideas and inferences about the casual relationship of interest (Seltman, 2018). However, the threat that was recognized can easily be addressed in design or measurement innovations. Clear, definitive and specific definitions were provided in this study, along with the attempt to reduce unnecessary jargon that may confuse the audience.

Ethical Procedures

According to the NHANES data guidelines, NHANES data collection adhered to the requirements of federal law. The Public Health Service Act (42 USC 242k) authorizes data collection and section 308(d) of that law (42 USC 242m), the Privacy Act of 1974 (5 USC 552A), and the Confidential Information Protection and Statistical Efficiency Act of 2002(PL 107-347) prohibit NCHS form releasing information that may identify respondents or groups of respondents (Centers of Disease Control and Prevention, 2018). To counteract the releasing of identities, data edits were made to some variables to reduce the risk of identification and exposure.

Additionally, in accordance with the Confidential Information Protection and Statistical Efficiency Act, every NCHS employee, contractor, and agent has taken an oath and is subject to a jail sentence for up to five years, a fine up to $250,000, or both if the party willfully discloses any identifiable information about the participants (National Center for Health Statistics, 2017). NCHS complies with the Federal Cybersecurity Act of 2015 (6 USC §§ 151 & 151 note). It requires the federal government to protect federal computer networks by using security programs to identify cybersecurity risks of hacking, internet attacks and other weaknesses (National Center for Health Statistics, 2017). Furthermore, the appropriate consent documents and brochures were presented and designed to help participants understand the NHANES survey and testing.

Lastly, the study was conducted when approval from the Walden University Institutional Review Board (IRB) was granted.

Summary

The study was aimed at investigating the possibility of a relationship between the predictor variables of certain endocrine disruptors (BPA, BPF, BPS, AA, GA) with the outcome variable of BMI while controlling for variables of race, income, fast food, food security category and access to health care. The correlational cross-sectional design was deemed appropriate for this study for numerous reasons: (a) the ability to measure independent and dependent variables simultaneously, (b) the ability to control for confounding variables, and (c) measuring the inclusivity of all variables with the set research questions that focus on levels of influence that affect the individual pertaining to the social-ecological model. The research design, methodology, and data analysis plan were based on the data provided by the NHANES 2015-2016 survey cycle. Linear multiple regression analysis, if the assumptions are met, will be used to analyze and interpret the relationships among the defined variables.

Section 3: Presentation of the Results and Findings

Introduction

The purpose of the study was to investigate if there was a relationship between the dependent variable of BMI and the independent variables of BPA, BPF, BPS, AA and GA, while controlling for the covariates (confounding variables) of race/ethnicity, income, fast food intake over 7 days, food security, and access to healthcare. In order to examine the relationship or association of the independent variables on the dependent variables while controlling for covariates, the following research questions were designed and finalized. Linear multiple regression, mentioned by Moran,(2013) was used to assess whether the set of independent variables were able to predict the dependent variable, hence why I decided the nature of the study design: correlational cross-sectional design.

Research Question 1 (RQ1): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for income?

Null Hypothesis ($H_0$1): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for income.

Alternative Hypothesis ($H_1$1):There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for income.

Research Question 2 (RQ2): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the race?

Null Hypothesis ($\mathrm{H}_0$2): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Alternative Hypothesis ($H_1 2$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Research Question 3 (RQ3): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza?

Null Hypothesis ($H_0 3$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Alternative Hypothesis ($H_0 3$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Research Question 4 (RQ4): What is the relationship among acrylamide, glycidamide, BPA, BPS, BPF and BMI while controlling for food security?

Null Hypothesis ($H_0 4$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Alternative Hypothesis ($H_1 4$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Research Question 5 (RQ5): What is the relationship among, AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year?

Null Hypothesis ($H_0 5$): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Alternative Hypothesis ($H_1 5$): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Data Collection of Secondary Data

The time frame for data collection was during the 2015–2016 NHANES cycle within the United States. I found that the NHANES dataset consisted of 15,327 persons who were selected from 30 different survey locations; of those selected, 9,971 persons completed the interview and 9,544 were examined (Centers for Disease Control and Prevention, 2020b). Of these figures, 61% were officially interviewed and 59% completed the health examination component of the NHANES.

Data Collection Procedures

The oversampled subgroups in the 2015–2016 NHANES are as follows: Hispanic persons, non-Hispanic Black persons, non-Hispanic Asian persons, non-Hispanic White and other persons at or below 185% of the Department of Health and Human Services poverty guidelines, and non-Hispanic White and other persons aged 80 years of age and older (Centers for Disease Control and Prevention, 2020b). To facilitate the oversampling of the Asian population, survey materials were translated into Korean, Vietnamese, and Mandarin Chinese (both Simplified and Traditional). I found the recorded and written translations on the NHANES website under the participants' webpage. In addition, a short video was provided to show the benefits to participating in the NHANES (Centers for Disease Control and Prevention, 2020b). The video was also available in Amharic, French, Haitian, Creole, Hindi and Spanish.

Dummy Coding and Data Cleaning

It was stated previously that the NHANES data were classified as downloadable public use files that were located on the Centers for Disease Control and Prevention website. No special permissions were needed to gain access to the NHANES dataset for cycle 2015–2016. However, because my study is analyzing certain factors (chemicals, BMI and variables of an environment), data had to be cleaned. Independent variables that had missing values were recoded as a value of -1 in discrete missing values, to ensure that missing values would be omitted from the SPSS calculations.

Table 3

Sociodemographic Profile of the Study Population

Characteristic	Frequency	Percentage
Times received healthcare over past year		
None	1421	14.3%
1	2049	20.5%
2-3	3140	31.5%
4-5	1487	14.9%
6-7	699	7.0%
8-9	271	2.7%
10-12	437	4.4%
13-15	133	1.3%
16 or more	304	3.0%
-1	30	.3%
Total	9971	100.0%
Race/Hispanic Origin		
Mexican American	1921	19.3%
Other Hispanic	1308	13.1%
Non-Hispanic White	3066	30.7%
Non-Hispanic Black	2129	21.4%
Non-Hispanic Asian	1042	10.5%
Other race-Including Multi-Racial	505	5.1%
Total	9971	100.0%
Fast Food intake in 7 days		
.00	1727	17.3%
1.00	2315	23.2%
2.00	1396	14.0%
3.00	727	7.3%
4.00	320	3.2%

Table 3 Continued

5.00	259	2.6%
6.00	82	.8%
7.00	155	1.6%
8.00	36	.4%
9.00	14	.1%
10.00	91	.9%
11.00	7	.1%
12.00	21	.2%
13.00	3	.0%
14.00	31	.3%
15.00	13	.1%
16.00	1	.0%
17.00	3	.0%
19.00	1	.0%
20.00	1	.0%
21.00	8	.1%
5555.00	2	.0%
-1	2758	27.7%
Total	9971	100.0%
Annual Income		
$0-$4,999	250	2.5%
$5,000-$9,999	373	3.7%
$10,000-$14,999	537	5.4%
$15,000-$19,999	600	6.0%
$20,000-$24,999	627	6.3%
$25,000-$34,999	1017	10.2%
$35,000-$44,999	960	9.6%
$45,000-$54,999	789	7.9%
$55,000-$64,999	629	6.3%
$65,000-$74,999	498	5.0%
$20,000 and over	292	2.9%
Under $20,000	146	1.5%
$75,000-$99,999	920	9.2%
$100,000 and over	1634	16.4%
-1	699	7.0%
Total	9971	100.0%
Food Security Category		

Table 3 Continued

Adult full food security	5717	57.3%
Adult marginal food security	1499	15.0%
Adult low food security	1417	14.2%
Adult very low food security	996	10.0%
-1	342	3.4%
Total	9971	100.0%

Univariate Analysis

I designed the study to test the significance of BMI and specific chemicals (BPA, BPF, BPS, AA and GA) while controlling for covariates; to examine the association of independent variables, the dependent variable and the confounding variables, the univariate test of a two-way ANCOVA, or an analysis of covariance was implemented.

Univariate statistics refer to all statistical analysis that include one single dependent variable with the inclusion of one or more independent variables, while including the use of covariates (Allen, 2017c). Univariate statistics allow the researcher to analyze and infer about a causal relationship between all variables and to generalize the results of the analysis that was conducted on a smaller sample to the larger population.

Statistical Strength

Two-way ANCOVA

Although the data analysis plan previously called for the use of multiple linear regression, the analysis of covariance (ANCOVA) statistical procedure was used for the sole purpose of providing additional statistical power as mentioned in Pourhoseingholi et al. (2012). ANCOVA is often used instead of the analysis of variance (ANOVA) procedure when covariates are involved in a study. ANCOVA is appropriate with covariates identified to control variables. ANCOVA is also useful with the application of regression models, to fit regressions where there are both categorical and interval independent variables (Lehigh University, n.d.). With ANCOVA, the independent variables in this particular circumstance utilizes categorical independent variables with the implementation of dummy variables (Lehigh University, n.d.). ANCOVA tests whether certain factors will have an effect on the dependent or outcome variable after removing the variance in quantitative covariates (Pourhoseingholi et al., 2012).

I used ANCOVA in an attempt to explain any nonrandom association between two or more variables, with covariates being simultaneously employed to control for additional variations. The purpose of me utilizing the two-way ANCOVA method was to determine whether there was an interaction effect between the categorical independent variables and the continuous dependent variable. ANCOVA was an ideal statistical technique that utilized extra variables to control for distracting, inferring or confounding variables that could distort the relationship between the independent variables and the dependent variable (Allen, 2017a). I found that the adjusted means (means that adjust or the covariates) were the main differences ANCOVA focused on.

In a two-way ANCOVA, the mean values of the groups of the independent variables are adjusted by the covariates. The statistical significance of the independent variables is based on the adjusted means, rather than the unadjusted means (Allen, 2017a). It is shown that even when adjusted for covariates, the means remain different, thus implying that there was a source of known or believed influence that may need to be removed as a source of influence to examine the underlying relationships (Allen, 2017a).

The covariate needs to have some sort of influence if it is to be identified as such. The unadjusted (descriptive statistics) and adjusted (estimates) tables are shown below to highlight the slightly different means. It is shown in the tables that the covariates were ideal for the research questions, the study continued with the use of multiple linear regression. Not only were the unadjusted and adjusted means different within the design, but the impact of the covariates was different for each cell.

Table 4

Two-Way ANCOVA-Unadjusted Mean and Standard Deviation

AA	GA	BPA	BPF	BPS	Mean	Std. Dev.	N
Below 3.90	Below 4.90	Below 0.2	Below 0.2	Below 0.1	25.8502	7.89065	4241
				0.1 and above	26.1167	4.45036	6
				Total	25.8505	7.88655	4247
			0.2 and above	Below 0.1	33.9000	.	1
				0.1 and above	23.3000	12.16224	2
				Total	26.8333	10.55525	3
			Total	Below 0.1	25.8521	7.89068	4242

		0.1 and above	25.4125	6.08099	8
		Total	25.8512	7.88714	4250
0.2 and above	Below 0.2	Below 0.1	26.2563	9.13141	16
		0.1 and above	26.7408	8.69394	103
		Total	26.6756	8.71567	119
	0.2 and above	Below 0.1	24.6500	7.74203	6
		0.1 and above	26.9092	7.98743	76
		Total	26.7439	7.94503	82
	Total	Below 0.1	25.8182	8.62359	22
		0.1 and above	26.8123	8.37861	179
		Total	26.7035	8.38953	201
Total	Below 0.2	Below 0.1	25.8517	7.89447	4257
		0.1 and above	26.7064	8.50428	109

			Total	25.8730	7.91035	4366
		0.2 and above	Below 0.1	25.9714	7.88495	7
			0.1 and above	26.8167	8.02450	78
			Total	26.7471	7.97007	85
		Total	Below 0.1	25.8519	7.89354	4264
			0.1 and above	26.7524	8.28577	187
			Total	25.8897	7.91150	4451
4.90 and above	Below 0.2	Below 0.2	Below 0.1	27.0500	6.94111	6
			Total	27.0500	6.94111	6
		Total	Below 0.1	27.0500	6.94111	6
			Total	27.0500	6.94111	6
	0.2 and above	Below 0.2	Below 0.1	30.7000	.	1
			0.1 and above	30.0444	10.04180	9

		Total	30.1100	9.46977	10
	0.2 and above	0.1 and above	26.3667	9.53494	12
		Total	26.3667	9.53494	12
	Total	Below 0.1	30.7000	.	1
		0.1 and above	27.9429	9.68590	21
		Total	28.0682	9.47073	22
Total	Below 0.2	Below 0.1	27.5714	6.48478	7
		0.1 and above	30.0444	10.04180	9
		Total	28.9625	8.49744	16
	0.2 and above	0.1 and above	26.3667	9.53494	12
		Total	26.3667	9.53494	12
	Total	Below 0.1	27.5714	6.48478	7
		0.1 and above	27.9429	9.68590	21

			Total	27.8500	8.88063	28
Total	Below 0.2	Below 0.2	Below 0.1	25.8518	7.88879	4247
			0.1 and above	26.1167	4.45036	6
			Total	25.8522	7.88471	4253
		0.2 and above	Below 0.1	33.9000	.	1
			0.1 and above	23.3000	12.16224	2
			Total	26.8333	10.55525	3
		Total	Below 0.1	25.8537	7.88883	4248
			0.1 and above	25.4125	6.08099	8
			Total	25.8529	7.88529	4256
	0.2 and above	Below 0.2	Below 0.1	26.5176	8.90690	17
			0.1 and above	27.0063	8.80554	112
			Total	26.9419	8.78543	129

	0.2 and above	Below 0.1	24.6500	7.74203	6
		0.1 and above	26.8352	8.15654	88
		Total	26.6957	8.10851	94
	Total	Below 0.1	26.0304	8.48659	23
		0.1 and above	26.9310	8.50544	200
		Total	26.8381	8.48883	223
Total	Below 0.2	Below 0.1	25.8545	7.89205	4264
		0.1 and above	26.9610	8.62822	118
		Total	25.8843	7.91373	4382
	0.2 and above	Below 0.1	25.9714	7.88495	7
		0.1 and above	26.7567	8.18357	90
		Total	26.7000	8.12496	97
	Total	Below 0.1	25.8547	7.89112	4271

				0.1 and above	26.8726	8.41919	208
				Total	25.9020	7.91832	4479
3.90 and above	Below 4.90	Below 0.2	Below 0.2	Below 0.1	23.2000	4.54313	10
				0.1 and above	21.1000	.	1
				Total	23.0091	4.35625	11
			Total	Below 0.1	23.2000	4.54313	10
				0.1 and above	21.1000	.	1
				Total	23.0091	4.35625	11
		0.2 and above	Below 0.2	Below 0.1	25.1000	8.90955	2
				0.1 and above	26.7889	7.89621	54
				Total	26.7286	7.85023	56
			0.2 and above	Below 0.1	22.9000	1.55563	2
				0.1 and above	27.3644	9.21763	45

		Total	27.1745	9.06382	47
	Total	Below 0.1	24.0000	5.37401	4
		0.1 and above	27.0505	8.48235	99
		Total	26.9320	8.38623	103
Total	Below 0.2	Below 0.1	23.5167	4.96494	12
		0.1 and above	26.6855	7.86027	55
		Total	26.1179	7.49383	67
	0.2 and above	Below 0.1	22.9000	1.55563	2
		0.1 and above	27.3644	9.21763	45
		Total	27.1745	9.06382	47
	Total	Below 0.1	23.4286	4.59288	14
		0.1 and above	26.9910	8.46035	100
		Total	26.5535	8.15571	114

4.90 and above	Below 0.2	Below 0.2	Below 0.1	25.3774	6.33841	93
			0.1 and above	27.4862	8.99542	29
			Total	25.8787	7.07699	122
		0.2 and above	Below 0.1	23.8200	5.08793	5
			0.1 and above	24.7100	7.86179	10
			Total	24.4133	6.87884	15
		Total	Below 0.1	25.2980	6.26823	98
			0.1 and above	26.7744	8.70462	39
			Total	25.7182	7.04569	137
	0.2 and above	Below 0.2	Below 0.1	25.8000	7.52971	64
			0.1 and above	26.5179	7.98582	593
			Total	26.4479	7.93989	657
			Below 0.1	28.0395	7.75097	38

	0.2 and above	0.1 and above	25.4886	7.63601	510
		Total	25.6655	7.66436	548
	Total	Below 0.1	26.6343	7.65230	102
		0.1 and above	26.0420	7.83932	1103
		Total	26.0921	7.82228	1205
Total	Below 0.2	Below 0.1	25.5497	6.82886	157
		0.1 and above	26.5630	8.03028	622
		Total	26.3588	7.80951	779
	0.2 and above	Below 0.1	27.5488	7.56730	43
		0.1 and above	25.4737	7.63338	520
		Total	25.6321	7.64160	563
	Total	Below 0.1	25.9795	7.02286	200
		0.1 and above	26.0670	7.86737	1142

			Total	26.0539	7.74495	1342
Total	Below 0.2	Below 0.2	Below 0.1	25.1660	6.20303	103
			0.1 and above	27.2733	8.91554	30
			Total	25.6414	6.92656	133
		0.2 and above	Below 0.1	23.8200	5.08793	5
			0.1 and above	24.7100	7.86179	10
			Total	24.4133	6.87884	15
		Total	Below 0.1	25.1037	6.14231	108
			0.1 and above	26.6325	8.63901	40
			Total	25.5169	6.90843	148
	0.2 and above	Below 0.2	Below 0.1	25.7788	7.49586	66
			0.1 and above	26.5405	7.97267	647
			Total	26.4700	7.92778	713

	0.2 and above	Below 0.1	27.7825	7.63843	40
		0.1 and above	25.6407	7.78351	555
		Total	25.7847	7.78604	595
	Total	Below 0.1	26.5349	7.57671	106
		0.1 and above	26.1250	7.89539	1202
		Total	26.1583	7.86803	1308
Total	Below 0.2	Below 0.1	25.4053	6.72240	169
		0.1 and above	26.5730	8.01095	677
		Total	26.3397	7.78095	846
	0.2 and above	Below 0.1	27.3422	7.46021	45
		0.1 and above	25.6242	7.77884	565
		Total	25.7510	7.76287	610
	Total	Below 0.1	25.8126	6.91129	214

				0.1 and above	26.1414	7.91716	1242
				Total	26.0931	7.77614	1456
Total	Below 4.90	Below 0.2	Below 0.2	Below 0.1	25.8439	7.88518	4251
				0.1 and above	25.4000	4.48330	7
				Total	25.8432	7.88051	4258
			0.2 and above	Below 0.1	33.9000	.	1
				0.1 and above	23.3000	12.16224	2
				Total	26.8333	10.55525	3
			Total	Below 0.1	25.8458	7.88522	4252
				0.1 and above	24.9333	5.86707	9
				Total	25.8439	7.88110	4261
		0.2 and above	Below 0.2	Below 0.1	26.1278	8.85337	18
				0.1 and above	26.7573	8.40263	157

		Total	26.6926	8.42586	175
	0.2 and above	Below 0.1	24.2125	6.61933	8
		0.1 and above	27.0785	8.43071	121
		Total	26.9008	8.33740	129
	Total	Below 0.1	25.5385	8.14745	26
		0.1 and above	26.8971	8.40116	278
		Total	26.7809	8.37526	304
Total	Below 0.2	Below 0.1	25.8451	7.88837	4269
		0.1 and above	26.6994	8.26969	164
		Total	25.8767	7.90347	4433
	0.2 and above	Below 0.1	25.2889	6.98327	9
		0.1 and above	27.0171	8.44715	123
		Total	26.8992	8.34395	132

		Total	Below 0.1	25.8439	7.88589	4278
			0.1 and above	26.8355	8.33300	287
			Total	25.9063	7.91745	4565
4.90 and above	Below 0.2	Below 0.2	Below 0.1	25.4788	6.35096	99
			0.1 and above	27.4862	8.99542	29
			Total	25.9336	7.04814	128
		0.2 and above	Below 0.1	23.8200	5.08793	5
			0.1 and above	24.7100	7.86179	10
			Total	24.4133	6.87884	15
		Total	Below 0.1	25.3990	6.28564	104
			0.1 and above	26.7744	8.70462	39
			Total	25.7741	7.02229	143
		Below 0.2	Below 0.1	25.8754	7.49533	65

0.2 and above		0.1 and above	26.5706	8.02148	602
		Total	26.5028	7.96903	667
	0.2 and above	Below 0.1	28.0395	7.75097	38
		0.1 and above	25.5088	7.67480	522
		Total	25.6805	7.69940	560
	Total	Below 0.1	26.6738	7.62523	103
		0.1 and above	26.0775	7.87673	1124
		Total	26.1275	7.85464	1227
Total	Below 0.2	Below 0.1	25.6360	6.80783	164
		0.1 and above	26.6127	8.06321	631
		Total	26.4112	7.82671	795
	0.2 and above	Below 0.1	27.5488	7.56730	43
		0.1 and above	25.4938	7.67154	532

			Total	25.6475	7.67636	575
		Total	Below 0.1	26.0333	6.99661	207
			0.1 and above	26.1009	7.90280	1163
			Total	26.0907	7.77030	1370
Total	Below 0.2	Below 0.2	Below 0.1	25.8356	7.85318	4350
			0.1 and above	27.0806	8.29946	36
			Total	25.8458	7.85675	4386
		0.2 and above	Below 0.1	25.5000	6.13547	6
			0.1 and above	24.4750	8.01988	12
			Total	24.8167	7.27577	18
		Total	Below 0.1	25.8351	7.85054	4356
			0.1 and above	26.4292	8.22482	48
			Total	25.8416	7.85398	4404

0.2 and above	Below 0.2	Below 0.1	25.9301	7.75298	83
		0.1 and above	26.6092	8.09650	759
		Total	26.5423	8.06136	842
	0.2 and above	Below 0.1	27.3739	7.63962	46
		0.1 and above	25.8042	7.83986	643
		Total	25.9090	7.83103	689
	Total	Below 0.1	26.4450	7.71412	129
		0.1 and above	26.2400	7.98707	1402
		Total	26.2573	7.96218	1531
Total	Below 0.2	Below 0.1	25.8374	7.85047	4433
		0.1 and above	26.6306	8.10105	795
		Total	25.9580	7.89344	5228
		Below 0.1	27.1577	7.45342	52

0.2 and above	0.1 and above	25.7798	7.83895	655
	Total	25.8812	7.81446	707
Total	Below 0.1	25.8527	7.84646	4485
	0.1 and above	26.2463	7.99221	1450
	Total	25.9488	7.88346	5935

Table 5

Adjusted Means and Standard Error

AA	GA	BPA	BPF	BPS	Mean	Std. Error	95% CI LL	95% CI UL
Below 3.90	Below 4.90	Below 0.2	Below 0.2	Below 0.1	25.848[a]	.121	25.610	26.085
				0.1 and above	26.094[a]	3.221	19.780	32.409
			0.2 and above	Below 0.1	33.734[a]	7.888	18.270	49.197
				0.1 and above	23.304[a]	5.578	12.370	34.238
			Below 0.2	Below 0.1	26.233[a]	1.972	22.367	30.099

		0.2 and above		0.1 and above	26.769[a]	.777	25.245	28.293
			0.2 and above	Below 0.1	24.797[a]	3.221	18.482	31.112
				0.1 and above	26.873[a]	.905	25.099	28.647
	4.90 and above	Below 0.2	Below 0.2	Below 0.1	27.097[a]	3.221	20.783	33.410
				0.1 and above	.[a,b]	.	.	.
			0.2 and above	Below 0.1	.[a,b]	.	.	.
				0.1 and above	.[a,b]	.	.	.
		0.2 and above	Below 0.2	Below 0.1	30.675[a]	7.889	15.211	46.140
				0.1 and above	30.023[a]	2.630	24.868	35.178
			0.2 and above	Below 0.1	.[a,b]	.	.	.
				0.1 and above	26.345[a]	2.277	21.881	30.809
3.90 and above	Below 4.90	Below 0.2	Below 0.2	Below 0.1	23.196[a]	2.494	18.307	28.086
				0.1 and above	20.837[a]	7.889	5.372	36.303

		0.2 and above	Below 0.1	.[a,b]	.	.	.
			0.1 and above	.[a,b]	.	.	.
	0.2 and above	Below 0.2	Below 0.1	25.078[a]	5.578	14.143	36.013
			0.1 and above	26.796[a]	1.074	24.690	28.901
		0.2 and above	Below 0.1	23.041[a]	5.579	12.104	33.978
			0.1 and above	27.359[a]	1.177	25.052	29.666
4.90 and above	Below 0.2	Below 0.2	Below 0.1	25.387[a]	.818	23.783	26.991
			0.1 and above	27.556[a]	1.465	24.683	30.428
		0.2 and above	Below 0.1	23.696[a]	3.530	16.776	30.617
			0.1 and above	24.826[a]	2.496	19.934	29.718
	0.2 and above	Below 0.2	Below 0.1	25.807[a]	.986	23.874	27.740
			0.1 and above	26.527[a]	.324	25.892	27.162
			Below 0.1	28.067[a]	1.280	25.557	30.577

	0.2 and above	0.1 and above	25.487[a]	.349	24.802	26.172

Though the adjusted means were somewhat promising for this analysis, the p values (significance) for the independent variables and covariates in the model were classified as insignificant, with p-values greater than 0.05 ($p > 0.05$). However, because this particular study will continue to study the effects of factors within ecological levels of an individual, the covariates will remain in the study.

Multiple Linear Regression

Statistical Assumptions

Multiple linear regression (multiple regression) expands on linear regression by including more than one independent variable to understand their association with the sole dependent variable. Multiple linear regression is able to reveal relationships or associations between multiple predictor variables, which can include confounding variables, and the single outcome variable (Allen, 2017b). Typically, in multiple linear regression, the question of how to manage other elements involved in the analysis and prediction is included as a means of utilizing covariates.

Covariates are variables that are possibly correlated with both or either the dependent or independent variables. In multiple regression analysis, it is speculated by the investigator that the covariates have an underlying relationship with either variables established. In the regression analysis, the covariate should not be a source of direct causality; the covariate should have some level of influence, but the understanding of the defined relationship is improved by removing the relationship form the analysis (Allen, 2017b). Thus, if no correlation is mentioned between the covariates and the independent and dependent variables in the equation, then no such influence exists. A lack of influence will postulate that the use of covariates will add little to no understanding of the relationship between the predictor variables and the dependent variable; there would be no harm nor gain. However, this is not to say that the covariates wouldn't be useful to some of the variables. Covariates are not required to function equally with all predictors and the dependent variable.

In order to understand all the variables for multiple linear regression, a mathematical equation is used:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_k X_k + \varepsilon$$

By trying to predict the outcome (X) based on the values of the set predictor variables (Y_i), the multiple linear regression model can assess multiple variables, which includes covariates and factors in the same model (Schroeder et al., 2017).

Covariate Selection

The covariates were selected based on the elements/factors that dealt with the social-ecological model in terms of analyzing the possible influencers across multiple levels: individual, family, community, and region. The covariates of race/ethnicity, income, healthcare, fast food and food security categories. These factors were meant to serve as a collective of influence upon an individual within the United States. Additionally, the covariates were not associated with the independent or dependent variables.

Statistical Assumptions and Diagnostics

The assumptions for multiple linear regression analysis are as follows: (a) linearity is assumed to exist; (b) equal variance needs to be present in the residuals of each level of the predictors, which encompasses the factor of homoscedasticity; (c) the residuals are normally distributed (this principle is described as multivariate normality), and (d) multiple regression also assumes that the independent variables are not highly correlated with each other; no multicollinearity should be present (Allen, 2017b).

Normality

In order to have valid inferences from the regression the residuals of the regression need to follow normal distribution. Normality is observed through a predicted probability (P-P) plot (Uriel, 2012). Since the residuals conform to the diagonal normality line indicated by the plot, the assumption of normality is not violated. This assumption can be tested by looking at the P-P plot of the model. The closer the dots lie to the diagonal line, the closer the normal residuals are distributed (Statistics Solutions, 2021). A horizontal band is indeed shown, which is a good indication, however, the line remains closely paralleled for a greater portion of the line. Though the residuals follow the diagonal line, and by no means violate the assumption, this should still be taken into consideration.

Homoscedasticity

Homoscedasticity refers to how the residuals are equally distributed, or whether they tend to be clenched together at some values and far apart at other values (Statistics Solutions, 2021). The graph plots the standardized values the model would predict, against the standardized residuals obtained. With the scatterplot, it can be clearly seen that there is no funnel shape shown; no funnel shape is a good indication that the assumption has not been violated.

Multicollinearity

Multicollinearity refers to when the predictor variables are highly correlated with each other. Multicollinearity can be tested with the variance inflation factor (VIF) values. The VIF values in the multiple linear regression were lower than 10, excluding the variables of AA and GA. Due to the unacceptable values above 10, the multicollinear variables were combined as stated in Kim (2019); with GA a metabolite of AA, this was appropriate. With the multicollinear variables combined, all of the VIFs in the multiple linear regression model were lower than 10, which means that there was little multicollinearity among the chemicals acting as independent variables in this particular study (Table 6) (Statistics Solutions, 2021). AA/GA was the new name of the variable.

Table 6

VIF Values

	Variable	VIF
RQ1		
	Income	1.001
	AA/GA	3.377
	BPA	8.010
	BPF	1.581
	BPS	6.774

RQ2		
	Race	1.001
	AA/GA	3.416
	BPA	7.999
	BPF	1.564
	BPS	6.817
RQ3		
	Fast Food/Pizza	1.000
	AA/GA	3.376
	BPA	8.069
	BPF	1.567
	BPS	6.919
RQ4		
	Food Security	1.001
	AA/GA	3.388
	BPA	7.963
	BPF	1.568
	BPS	6.795
RQ5		
	Healthcare	1.001
	AA/GA	3.430
	BPA	7.986

BPF	1.564
BPS	6.796

Undue Influence

The influential cases biasing assumption tests for undue influence on the model which is measured by the Cook's Distance statistic. Any values that are over 1 are likely to be significant outliers, which have the potential to have unwanted influence on the model and should be removed from the analysis if applicable (Uriel, 2012). In this case, no such instances have occurred.

Durbin-Watson

The model summary box is needed to test this assumption. This assumption tests for the independence of the residuals. The statistic has the tendency to vary from 0 to 4. For this assumption to be met, the value needs to be close to 2 (Uriel, 2012). Values that are below 1 and above 3 are cause for concern (Uriel, 2012). However, this was not the case since the Durbin-Watson statistic is above 1 and below 2. The assumption has been met.

Results for Multiple Linear Regression

To answer the research questions provided, a multiple linear regression was conducted to test all hypotheses in question.

Research Question 1

Research Question 1 (RQ1): What is the relationship among AA/GA, BPA, BPS, BPF and BMI while controlling for income?

Null Hypothesis (H_01): There will be no significant relationship between AA/GA, BPA, BPS, BPF and BMI while controlling for income.

Alternative Hypothesis (H_11): There will be a significant relationship between AA/GA, BPA, BPS, BPF and BMI while controlling for income.

The results of the regression identify that the percent of variability in both models increased by a miniscule margin (.000% to .001%). Within the ANOVA table, neither the first nor second model predicted the scores on the dependent variable to make the decision statistically significant. Although, close to significant results were shown in model 2. It should be noted that model 1 focused on items in the research question that had to be controlled for, while model 2 encompassed the items that were defined as independent variables (Table 7).

Table 7

RQ1: Multiple Linear Regression Models

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	73.421	1	73.421	1.150	.284
	Residual	519784.389	8142	63.840		
	Total	519857.811	8143			
2	Regression	683.089	6	113.848	1.784	.098
	Residual	519174.722	8137	63.804		
	Total	519857.811	8143			

Table 8

Results of Regression with Annual Income

Predictor Variables		*B*	*β*	*t*	*p*
1	Annual Income	.022	.012	1.072	.284
2	Annual Income	.020	.011	1.008	.313
	AA and GA	-.377	-.040	-1.952	.051
	BPA LLOD	1.249	.069	2.187	.029
	BPF LLOD	-.515	-.021	-1.509	.131
	BPS LLOD	-.090	-.005	-.169	.866

Note.*$p < .05$

The multiple linear regression was carried out to determine if annual income and the independent variables of AA, GA, BPA, BPF, and BPS could significantly impact the dependent variable of body mass index. In Table 7, the two applied regression models are presented: Model 1 containing the covariate of annual income had a statistically insignificant effect and proportion of variance, $R^2 = .000$, F (1, 8142) = 1.150, $p > 0.05$. Model 2, which contained the independent variables, also had an insignificant effect with a very miniscule difference in variance, $R^2 = .001$, F (5, 8138) = 2.134, $p > 0.05$. Interestingly, the coefficient table suggested that BPA had a statistically significant p-value of 0.028 ($p < 0.05$) (Table 8), this is enough to deem the relationship between BPA and BMI, while controlling for income, as significant. Additionally, AA and GA nearly had a statistically significant value, but was still rendered insignificant. Therefore, there is a statistically significant relationship between the independent variable of BPA and the dependent variable while controlling for income; the study will accept the alternative hypothesis and reject the null hypothesis.

Table 9

Multiple Linear Regression Analysis Between AA/GA, BPA, BPF, BPS and BMI while controlling for income

Predictor	*B*	95% CI	*b*	*t*	*p*
Annual Income	.020	-.019, .060	.011	1.008	.313
AA and GA	-.377	-1.766, .769	-.040	-1.952	.051
BPA	1.249	.135, 2.381	.060	2.187	.029
BPF	-.515	-1.184, .154	-.021	-1.509	.131
BPS	-.090	-1.134, .962	-.005	-.169	.866

Figure 1

P-P Plot for Income

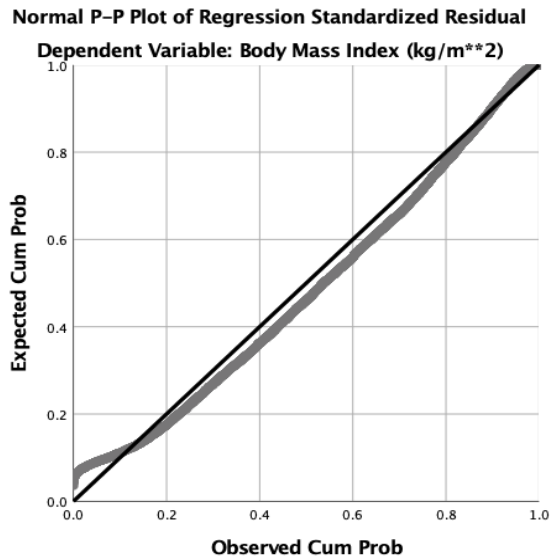
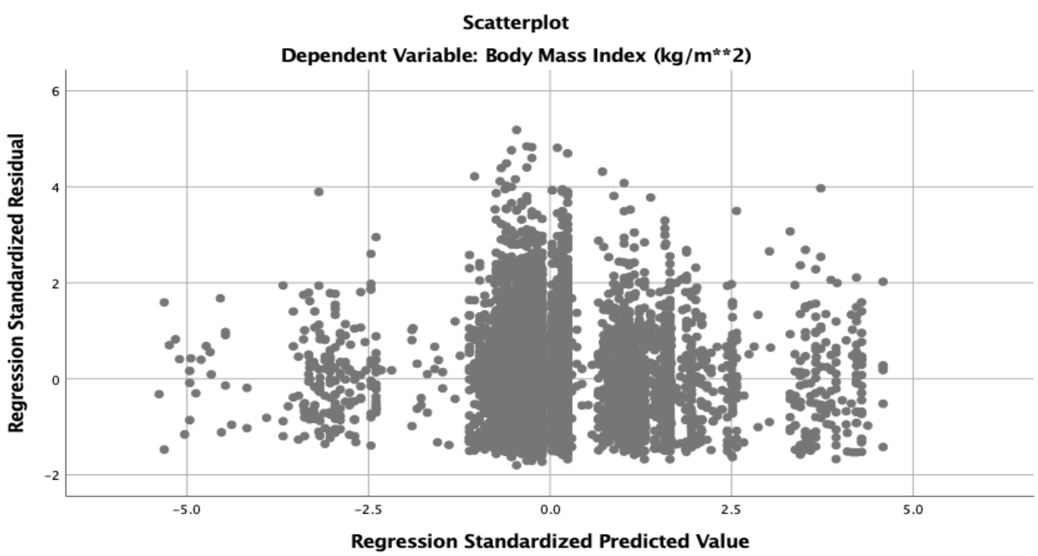


Figure 2

Scatterplot for Income



Research Question 2

Research Question 2 (RQ2): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the race?

Null Hypothesis (H_02): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

Alternative Hypothesis (H_12): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for race.

The results of the regression identify that the percent of variability in both models increased by a miniscule margin (.000% to .001%). Within the ANOVA table 10, neither the first nor second model predicted the scores on the dependent variable to make the decision statistically significant. It should be noted that model 1 focused on items in the research question that had to be controlled for, while model 2 encompassed the items that were defined as independent variables (Table 10).

Table 10

RQ2: Multiple Linear Regression Models

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	51.841	1	51.841	.817	.366
	Residual	555218.978	8754	63.425		
	Total	555270.819	8755			
2	Regression	687.070	5	137.414	2.168	.055
	Residual	554583.749	8750	63.381		
	Total	555270.819	8755			

Table 11

Results of Regression with Race

Predictor Variables	***B***	***β***	***t***	***p***

1	Race	.046	.010	.904	.366
2	Race	.050	.011	.000	.318
	AA and GA	-.381	-.040	-2.044	.041
	BPA LLOD	1.158	.064	2.116	.034
	BPF LLOD	-.573	-.023	-1.754	.080
	BPS LLOD	-.007	.000	-.014	.989

Note.*$p < .05$

The multiple linear regression was carried out to determine if race and the independent variables of AA, GA, BPA, BPF, and BPS could significantly impact the dependent variable of body mass index. Model 1 containing the covariate of race had a statistically insignificant effect and the proportion of variance, $R^2 = .000$, F (1, 8754) = .817, $p > 0.05$. Model 2 also had statistically insignificant results: $R^2 = .001$, F (5, 8750) = 2.168, $p > 0.05$. Additionally, all variables, excluding AA and GA and BPA, had insignificant results ($p > 0.05$), with the variable of BPA having significant p-value of .034 ($p < 0.05$) and AA and GA having a significant p-value of .041 ($p < 0.05$) (Table 11). The final result being that there is a statistically significant relationship between the independent variables and the dependent variable while controlling for race; the study will reject the null hypothesis.

Table 12

Multiple Linear Regression Analysis Between AA/GA, BPA, BPF, BPS and BMI while controlling for race

Predictor	*B*	*95% CI*	*b*	*t*	*p*
Race	.050	-.049, .149	.011	.999	.318
AA and GA	-.381	-.746, -.016	-.040	-2.044	.041
BPA	1.158	.095, 2.231	.064	2.116	.034
BPF	-.573	-1.214, .068	-.023	-1.754	.080
BPS	-.007	-1.014, .999	.000	-.014	.989

Figure 3

P-P Plot for Race

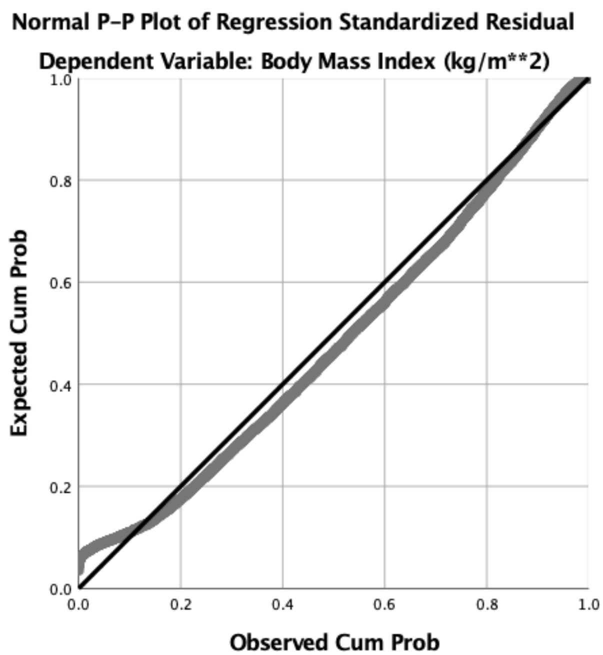
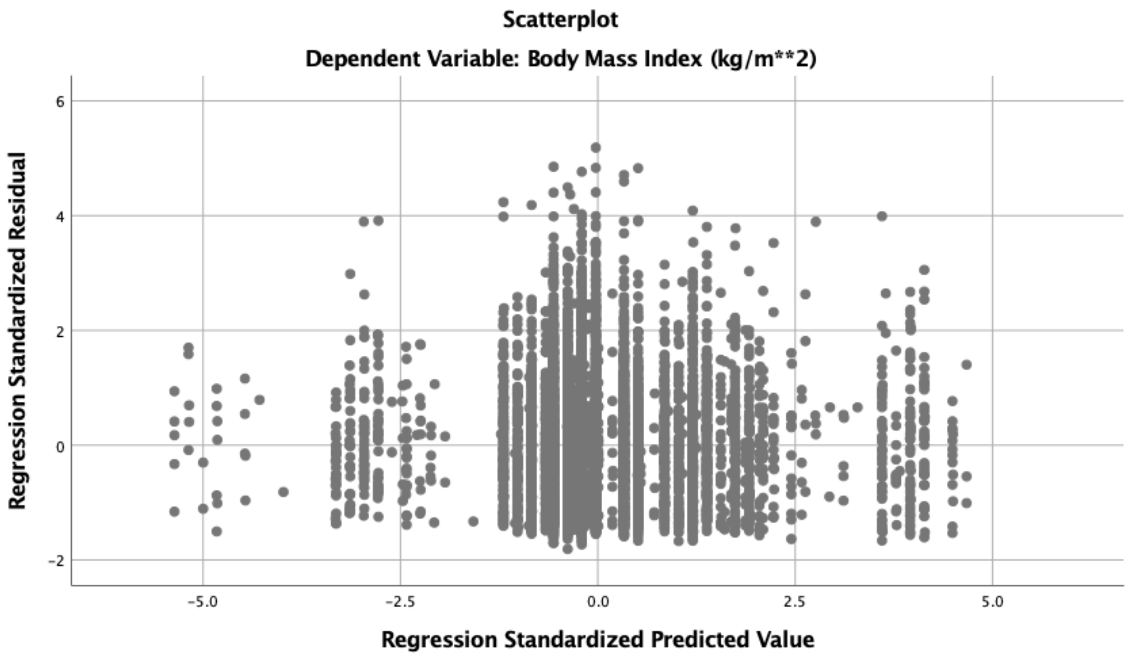


Figure 4

Scatterplot for Race



Research Question 3

Research Question 3 (RQ3): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza?

Null Hypothesis ($H_0$3): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

Alternative Hypothesis ($H_0$3): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza.

The results of the regression identify that the percent of variability in both models increased by a miniscule margin (.000% to .001%). Within the ANOVA table 13, neither the first nor second model predicted the scores on the dependent variable to make the decision statistically significant. It should be noted that model 1 focused on items in the research question that had to be controlled for, while model 2 encompassed the items that were defined as independent variables (Table 13).

Table 13

RQ3: Multiple Linear Regression Models

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	43.428	1	43.428	.702	.402
	Residual	392822.153	6353	61.833		
	Total	392865.580	6354			
2	Regression	477.445	5	95.489	1.545	.172
	Residual	392388.135	6349	61.803		
	Total	392865.580	6354			

Table 14

Results of Regression with Fast Food Intake

	Predictor Variables	***B***	***β***	***t***	***p***
1	Fast Food	-.001	-.011	-.838	.402
2	Fast Food	-.001	-.010	-.827	.408
	AA and GA	-.283	-.030	-1.316	.188
	BPA LLOD	.871	.049	1.365	.172
	BPF LLOD	-.594	-.024	-1.558	.119
	BPS LLOD	.235	.013	.391	.696

The multiple linear regression was carried out to determine if fast food intake over seven days and the independent variables of AA, GA, BPA, BPF, and BPS could significantly impact the dependent variable of BMI. Model 1 with the covariate had a statistically insignificant effect: R^2 = .000, F (1, 6353) = .702, p > 0.05. Model 2 also had a statistically insignificant effect: R^2 = .001, F (5, 6349) = 1.545, p > 0.05. The coefficient table marked that all variables were deemed insignificant (Table 14). The result is that there is no statistically significant relationship between the independent variables and the dependent variable while controlling for fast food intake of seven days; the study failed to reject the null hypothesis.

Table 15

Multiple Linear Regression Analysis Between AA/GA, BPA, BPF, BPS and BMI while controlling for intake of fast food

Predictor	*B*	95% CI	*b*	*t*	*p*
Fast Food	-.001	-.004, .002	-.010	-.827	.408
AA and GA	-.283	-.705, .139	-.030	-1.316	.188
BPA	.871	-.380, 2.123	.049	1.365	.172
BPF	-.594	-1.342, .153	-.024	-1.558	.119
BPS	.235	-.943, 1.413	.013	.391	.696

Figure 6

P-P Plot for Fast Food

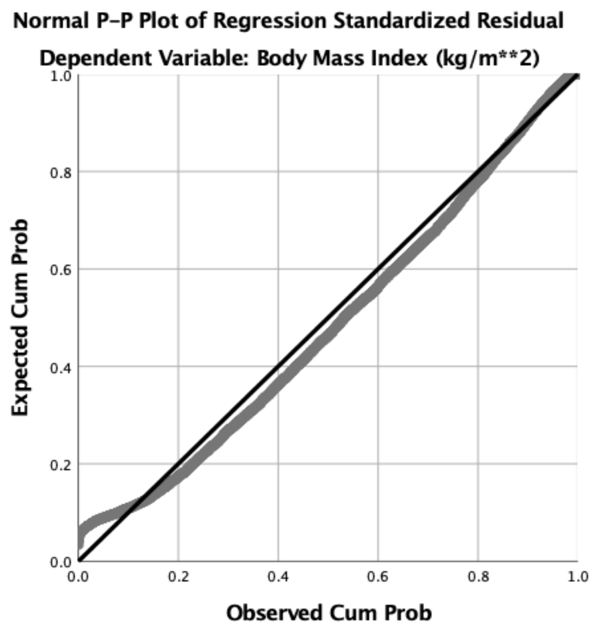
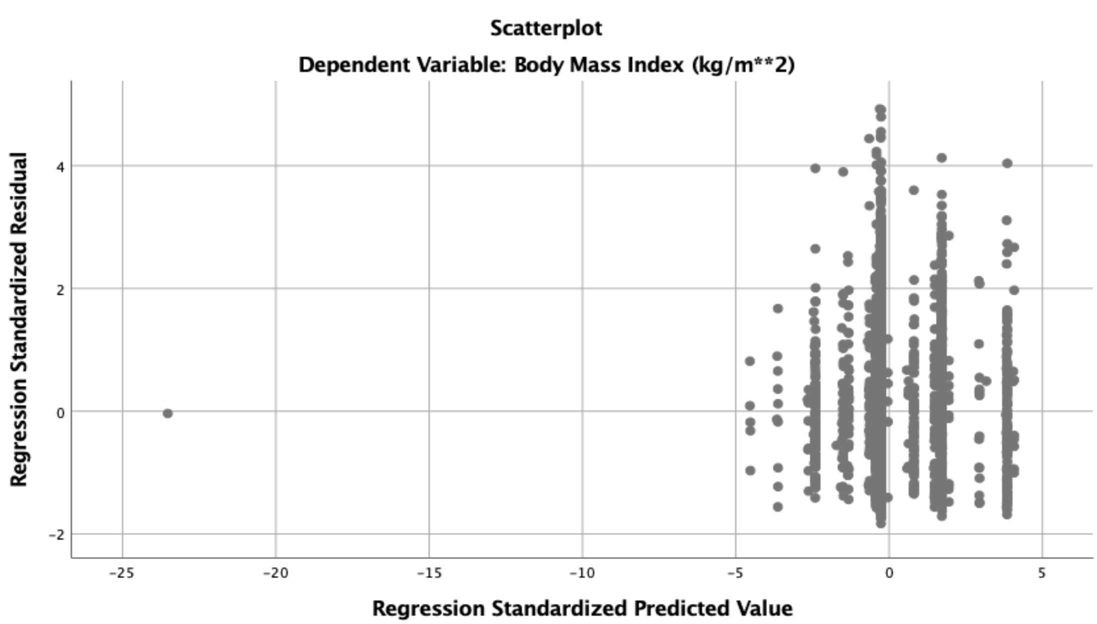


Figure 5

Scatterplot for Fast Food



Research Question 4

Research Question 4 (RQ4): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for food security?

Null Hypothesis ($H_0$4): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

Alternative Hypothesis ($H_1$4): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for food security.

The results of the regression identify that the percent of variability in both models increased by a miniscule margin (.000% to .001%). Within the ANOVA table 16, neither the first nor second model predicted the scores on the dependent variable to make the decision statistically significant. It should be noted that model 1 focused on items in the research question that had to be controlled for, while model 2 encompassed the items that were defined as independent variables.

Table 16

RQ4: Multiple Linear Regression Models

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	.726	1	.726	.011	.915
	Residual	538044.221	8446	63.704		
	Total	538044.947	8447			
2	Regression	521.726	5	104.345	1.639	.146
	Residual	537523.220	8442	63.672		
	Total	538044.947	8447			

Table 17

Results of Regression with Food Security

	Predictor Variables	***B***	***β***	***t***	***p***
1	Food Security	.009	.001	.107	.915
2	Food Security	.010	.001	.126	.900
	AA and GA	-.350	-.037	-1.845	.065
	BPA LLOD	1.112	.061	1.993	.046
	BPF LLOD	-.465	-.019	-1.390	.164
	BPS LLOD	-.050	-.003	-.095	.925

Note. *p <.05

The multiple linear regression was carried out to determine if food security category and the independent variables of AA, GA, BPA, BPF, and BPS could significantly impact the dependent variable of BMI. Model 1 had results that were deemed statistically insignificant: R^2 = .000, F (1, 8446) = .011, p > 0.05. Model 2 has similar results: R^2 = .001, F (5, 8442) = 1.639, p > 0.05 (Table 16). Additionally, all variables, excluding BPA, had insignificant results (p > 0.05). BPA had a significant p-value of .046 (p < 0.05) (Table 17). The final result being that there is a statistically significant relationship between the independent variables and the dependent variable while controlling for food security; the study succeeded in rejecting the null hypothesis.

Table 18

Multiple Linear Regression Analysis Between AA/GA, BPA, BPF, BPS and BMI while controlling for food security

Predictor	*B*	*95% CI*	*b*	*t*	*p*
Food Security	.010	-.152, .173	.001	.126	.900
AA and GA	-.350	-.721, .022	-.037	-1.845	.065
BPA	1.112	.018, 2.205	.061	1.993	.046
BPF	-.465	-1.119, .190	-.019	-1.390	.164
BPS	-.050	-1.076, .977	-.003	-.095	.925

Figure 7

P-P Plot for Food Security

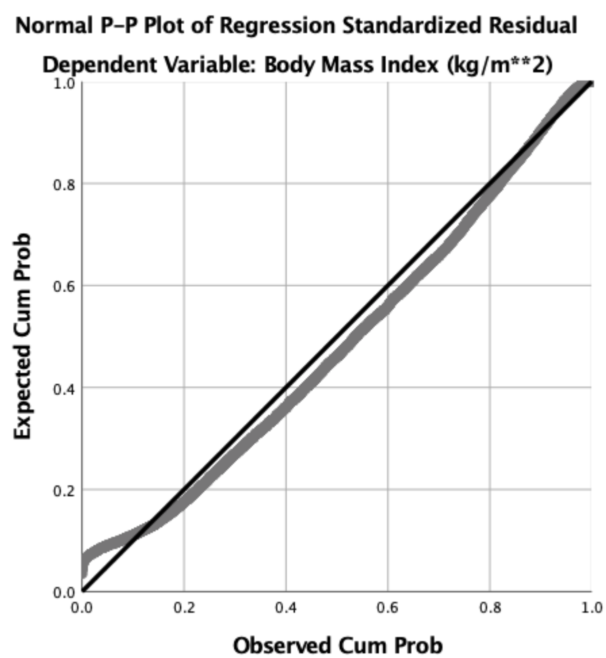
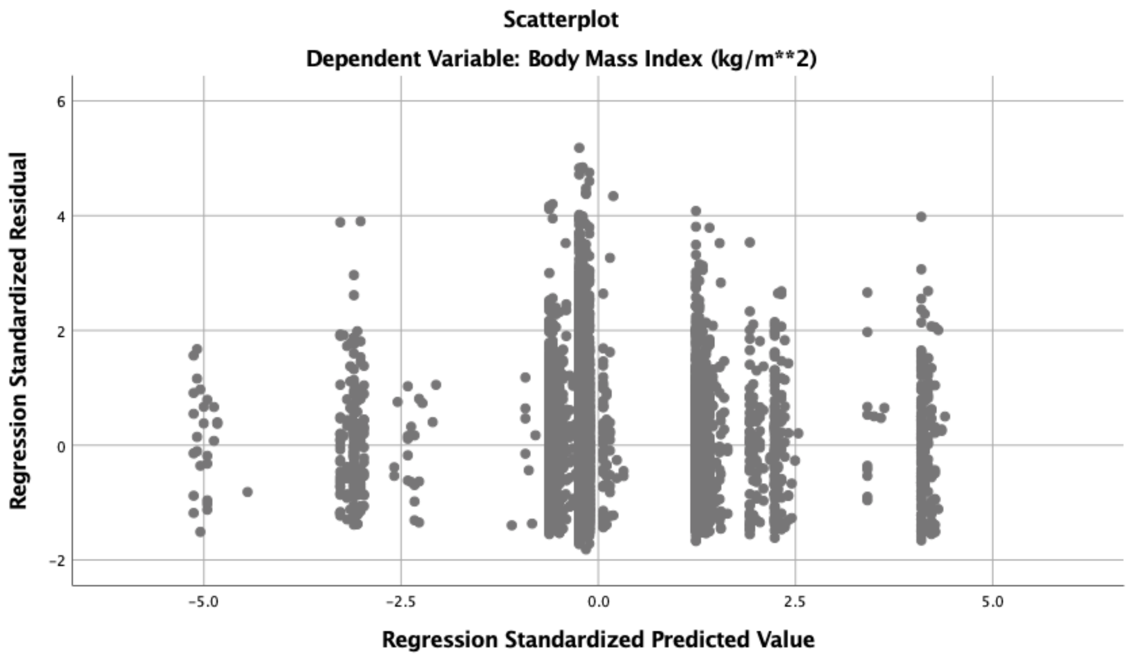


Figure 8

Scatterplot for Food Security



Research Question 5

Research Question 5 (RQ5): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year?

Null Hypothesis ($H_0$5): There will be no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

Alternative Hypothesis ($H_1$5): There will be a significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year.

The results of the regression identify that the percent of variability in both models increased by a miniscule margin (.000% to .001%). Within the ANOVA table 19, neither the first nor second model predicted the scores on the dependent variable to make the decision statistically significant. It should be noted that model 1 focused on items in the research question that had to be controlled for, while model 2 encompassed the items that were defined as independent variables.

Table 19

RQ5: Multiple Linear Regression Models

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	72.628	1	72.628	1.148	.284
	Residual	552270.565	8727	63.283		
	Total	552343.194	8728			
2	Regression	652.993	5	130.599	2.065	.067
	Residual	551690.200	8723	63.245		
	Total	552343.194	8728			

Table 20

Results of Regression of Healthcare

	Predictor Variables	***B***	***β***	***t***	***p***
1	Healthcare	.049	.011	1.071	.284
2	Healthcare	.051	.012	1.120	.263
	AA and GA	-.333	-.035	-1.784	.075

BPA LLOD	1.121	.062	2.049	.041
BPF LLOD	-.602	-.025	-1.839	.066
BPS LLOD	-.050	-.003	-.098	.922

Note.**p* < .05

The multiple linear regression was carried out to determine if the times an individual has received healthcare and the independent variables of acrylamide, glycidamide, BPA, BPF, and BPS could significantly impact the dependent variable of body mass index. Model 1 had results that were deemed statistically insignificant: R^2 = .000, *F* (1, 8727) = 1.148, *p* > 0.05 (Table 19). Model 2 results were also deemed insignificant: R^2 = .001, F (5, 8723) = 2.065, p > 0.05. Additionally, all variables in model 2, excluding BPA, had insignificant results (*p* > 0.05). However, BPA had a significant p-value of .041 (*p* < 0.05) (Table 20). The final result being that there is a statistically significant relationship between the independent variables and the dependent variable while controlling for the times an individual; the null hypothesis is rejected.

Table 21

Multiple Linear Regression Analysis Between AA/GA, BPA, BPF, BPS and BMI while controlling for healthcare over the past year

Predictor	*B*	95% CI	*b*	*t*	*p*
Healthcare	.051	-.038, .141	.012	1.120	.263
AA and GA	-.333	-.699, .033	-.035	-1.784	.075
BPA	1.121	.048, 2.194	.062	2.049	.041
BPF	-.602	-1.243, .040	-.025	-1.839	.066
BPS	-.050	-1.056, .955	-.003	-.098	.922

Figure 9

P-P Plot for Healthcare

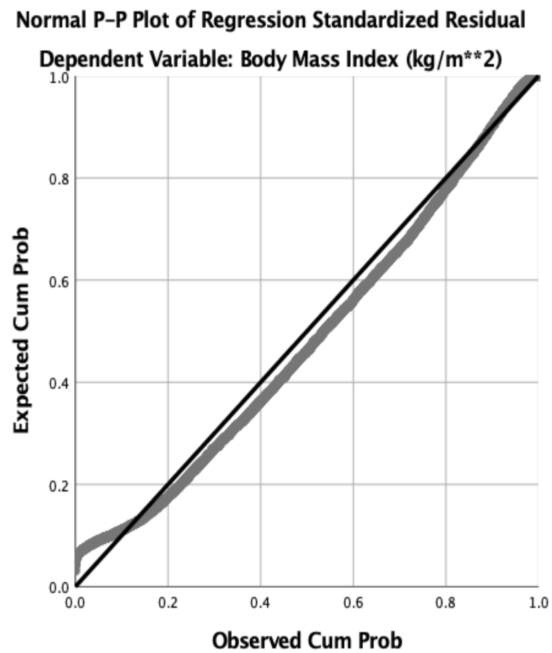
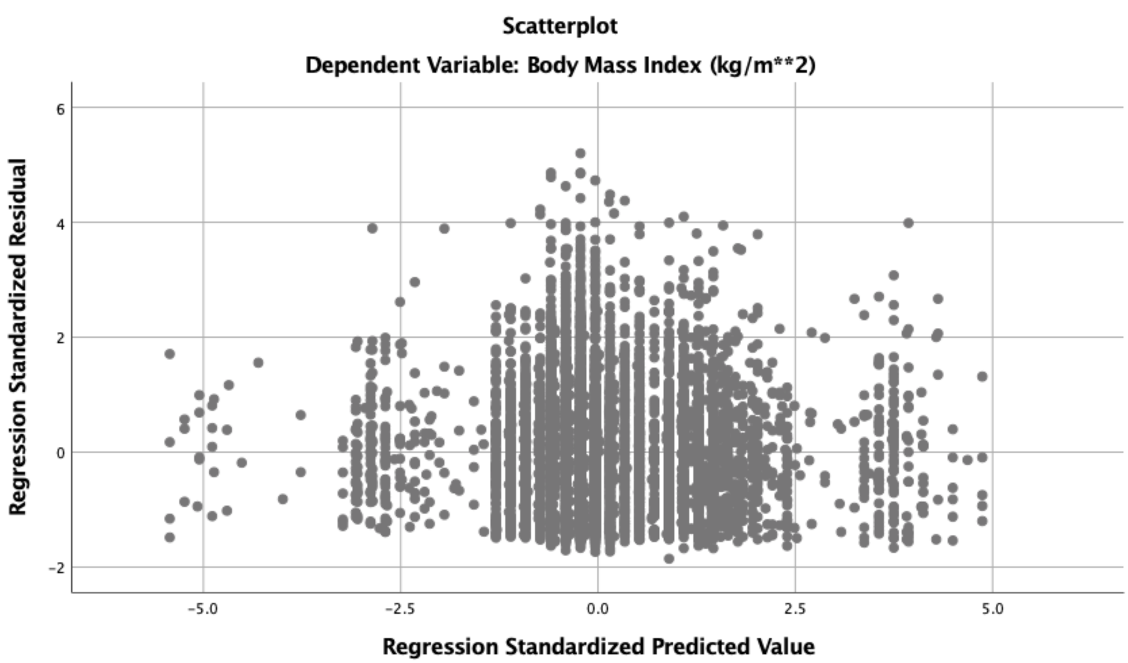


Figure 10

Scatterplot for Healthcare



Final Decisions for Statistical Analyses

Research Question 1 (RQ1): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for income?

Alternative Hypothesis ($H_1$1): There was a significant relationship between BPA and BMI while controlling for income.

Research Question 2 (RQ2): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the race?

Alternative Hypothesis ($H_1$2): There was a significant relationship between AA/GA and BPA and BMI while controlling for race.

Research Question 3 (RQ3): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for intake of fast food and pizza?

Null Hypothesis ($H_0$3): There was no significant relationship between AA, GA, BPA, BPS, BPF and BMI while controlling for the intake of fast food and pizza.

Research Question 4 (RQ4): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for food security?

Alternative Hypothesis ($H_1$4): There was a significant relationship between BPA and BMI while controlling for food security.

Research Question 5 (RQ5): What is the relationship among AA, GA, BPA, BPS, BPF and BMI while controlling for the times received health care over the past year?

Alternative Hypothesis ($H_1$5): There was a significant relationship between BPA and BMI while controlling for the times received health care over the past year.

Summary

The aim of this study was to examine and determine whether there was a relationship between specific endocrine disrupting chemicals of AA, GA, BPA, BPF and BPS with BMI while controlling for the variables of fast-food intake, race, annual income, access to health care, and food security category. Though results proved that there was no relationship between most of the independent variables, BPA is the exception to this statement with AA/GA having significant results in the second research question.

The answers to the research questions suggest that BPA has a higher tendency to have a relationship with weight, hence the use of the dependent variable of BMI, with AA/GA having a tendency to have a relationship with the independent variable of race. Even while controlling for income, race, food security, and health care, it is shown that there is a significant relationship between BPA, proving that such a relationship exists, and further examination is needed to probe this subject matter. AA/GA proved to have a miniscule positive relationship between race and BMI. Even though the two other independent variables of BPF, BPS produced insignificant results for all the research questions, the research is still worthy of exploration and may have further merit in future quantitative studies. With the positive relationship among BPA and BMI established, and similar results for AA/GA, this serves as further verification that endocrine disruptors remain a consistent public health issue as more information continues to be circulated in peer-reviewed journal articles at a frequent rate.

Section 4 will include the complete interpretation of findings and how said findings compare to existing data in previous studies, the appropriateness and interpretation of the theoretical framework, limitations of the study, recommendations for future research, and possible implications for social change.

Section 4: Application to Professional Practice and Implications for Social Change

Introduction

The purpose of this study was to analyze and evaluate the possibility of a relationship between the independent variables of BPA, BPF, BPS, AA/GA with the dependent variable of BMI while controlling for several covariates; the covariates consisted of race/ethnicity, income, food security category, intake of fast food, and access to healthcare. Endocrine disrupting chemicals are substances that display a negative interference with the endocrine system in terms of hormone action and the inflation of adipose tissue. These disturbances in hormones can be attributed to diseases throughout the human lifespan (Egusquiza & Blumberg, 2020).

Though BPA and its two analogues of BPF and BPS are somewhat correlated with obesity according to recent articles, the lack of definitive proof only added to ambiguous interpretations in the scientific community. This is the same for AA and its metabolite of GA; peer-reviewed studies indicated that some underlying correlation did exist between the chemicals and obesity. Unfortunately, present analyses remain inconsistent in terms of determining whether endocrine disruptors have a positive relationship in obesity (Jacobson et al., 2019). Regardless, all five of the chemicals need to be evaluated due to endocrine disruptors possessing the capacity to be located in food, food processing and packaging, water, plastics, thermal paper, and personal care products (Adani et al., 2020; Kassotis et al., 2020).

In this correlational, cross-sectional quantitative study, the chemicals were analyzed in order to establish if there was any sort of relationship between them and the dependent variable of body mass index while identifying and controlling for the confounding variables. The research design, methods and data analyses were based on the use of the NHANES survey from the 2015–2016 cycle dataset. Two-way ANCOVA and linear multiple regression were used to investigate the possible association between each independent variable and the dependent variable while establishing awareness of the confounding variables, respectively.

Interpretation of the Findings

The study findings showed that overall, a relationship did exist between BPA and BMI while controlling for the specific confounding variables of each research question; the same can be said to a certain extent with AA/GA when controlling for race. It should be noted that the endocrine disruptors of BPA and AA/GA were the only independent variables with significant results ($p < 0.05$); all other independent variables of BPF and BPS had no significant results.

The significant results with BPA support the hypothesis that the chemical is among, if not, the most common endocrine disruptor and disperses negative effects on receptors within human tissue (Zahra et al., 2020). Though there are efforts to distance the population from BPA, it is difficult with the chemical’s near omnipotence in society and in the environment. Furthermore, the significant results parallel to how BPA is able to bind to and interfere with actions of peroxisome proliferator-activated receptors (PPARs; (Darbre, 2020). BPA is typically regarded as one of the most frequently detected pollutants in the world and is slowly being recognized as a factor in the increasing development of cardio-metabolic diseases, including increased adiposity and weight gain (Zahra et al., 2020). Even at low dosages, BPA is a public health concern that remains consistent (Colorado-Yohar et al., 2021). These significant results are similar to that of Lehmler et al. (2018). The authors, while analyzing the exposure levels of bisphenols A, F, and S, found that median levels of BPA were higher amongst both adults and children than that of the BPF and BPS levels.

The insignificant results of this study coincide with that of Lee (2018), which acknowledges that systematic reviews and meta-analyses with endocrine disrupting chemicals can result in inconsistent results. However, another peer-reviewed article articulated that there is a possibility that BPA influences adipogenesis (the formation of adipocytes) as a PPARγ agonist, or substance that initiates (Egusquiza & Blumberg, 2020). Other studies mentioned in Lee (2018) proposed that BPA may induce obesogenic effects indirectly through its ability to bind to estrogen receptors and interfere with estrogen hormone signaling.

The other chemical that had marginally significant results was BPF. BPF had near significant results when controlling for the covariates of race/ethnicity and healthcare with *p*-values of 0.079 and 0.066, specifically. According to Lehmler et al. (2017), as mentioned in Egusquiza and Blumberg (2020), even though BPA is becoming more associated with obesity incidence levels, the analogues of BPF and BPS were not linked in a cross-sectional study of adults after adjusting for socioeconomic factors. Interestingly, BPF and BPS produced a positive association with obesity in children (ages 6–19).

Even though AA and GA have been identified as new endocrine disruptors, not much is available as of yet in terms of determining a correlation with AA/GA and obesity. So far, it has been documented by Equsquiza and Blumberg (2020) that both chemicals have the potential to act as obesogenic compounds that inhibit hormone activity. The significant results with AA/GA support the hypothesis that AA and its metabolite of GA have the potential to act as endocrine disruptors that alter hormonal balance (Adani et al., 2020). It is documented that AA acts as an endocrine disruptor in mice models, but there is speculation as to whether AA will act as an endocrine disruptor in human models (Amato et al., 2021; Oliveira et al., 2020). Though Amato et al, (2021) recently mentioned how AA is a verified obesogen with possible mechanisms of action, confounding variables must be resolved in order to establish a link between AA and obesity. Further exploration of said issues could be very beneficial to public health practice. The same is applicable for its metabolite of GA. More relevant research is needed to interpret the full extent of any relationship between AA/GA and obesity.

Interpretation of Findings in Theoretical Framework

The social-ecological model is a framework for understanding the interactive effects of personal and environmental factors that determine behaviors (Jernigan et al., 2018). As such, it is appropriate to use the model to analyze and determine any levels of influence in terms of exposure to endocrine disrupting chemicals and body mass index (used to measure for obesity).

Furthermore, the social-ecological model was ideal for looking at factors of heath at the individual, intrapersonal, organizational, and community levels. This fits in the narrative of the study due to the fact that obesity has multiple comorbidities, not just one single cause, hence the in-depth analysis of specific endocrine disrupting chemicals that have been associated with obesity (Lee & Blumberg, 2019). Due to the nature of the social-ecological model, certain confounding variables were identified as influential factors that could potentially skew the results of the study, as mentioned in Liu et al., (2017).

Limitations of the Study

Limitations that could impede the generalization of the secondary dataset is the nature of endocrine disrupting chemicals. Endocrine disrupting chemicals are at times notorious for their unpredictability in systematic reviews and meta-analyses despite evidence stated from in vitro and in vivo studies. This tends to happen with endocrine disruptors with short half-lives, the unpredictability of net effects of mixtures of endocrine disruptors, non-monotonic dose response, the nonexistence of a nonexposure group, primarily when the substances in question are in wide use in society and the interactions with established risk factors (Lee, 2018).

Additional limitations include the limited meaning of BMI from the NHANES. Instead of using the standard BMI variable of kilograms divided by the square of height in meters that is provided in the dataset, the utilization of waist circumference, standing height and weight measured in kilograms. Furthermore, cross-sectional research only distinguishes association, not causation. It should also be noted that the investigation among these endocrine disrupting chemicals while controlling for the covariates would produce different independent results if the covariates were omitted. Lastly, self-reported measurement bias pertaining to recall and information bias can arise from misclassification and participants providing erroneous information as indicated in (Althubaiti, 2016)

Recommendations

Recommendations for further research consist of how the current topic of discussion includes the notion of how people in society will never be free from the methodological issues that accompany omnipresent endocrine disrupting chemicals. Because of this predicament, it may be beneficial to evaluate early-life exposure during critical periods, which could be key to the development evolutionary aspects with epigenic programming (Lee, 2018). Harms due to continuous exposure during the noncritical periods may be avoided if an individual considers adopting a healthy lifestyle that counteracts the effects of endocrine disruptors; however, research needs to be done to test that hypothesis.

Additional studies should be implemented to analyze a possible relationship with obesity, BPA, its analogues and specific age groups. Other research that may have merit is endocrine disrupting chemical exposure level and race; previous research identified that significant results were present in non-Black Hispanics and Mexican Americans when compared to other racial groups within the United States (Attina et al., 2019). Lastly, it is recommended that other researchers culminate additional information that relates to AA, GA, obesity and human models, if said information is available.

Implications for Professional Practice and Social Change

Exposure to endocrine disruptors in adulthood can potentially alter the physiology of the endocrine system and disrupt the dispersing of hormones within the body. Although endocrine disruptors are still relatively unknown to the public, this topic needs to be taken into some serious consideration, especially when exposure to endocrine disruptors is continuous. With continuous exposure, the risk of endocrine disrupting chemical related diseases intensifies (Lee, 2018). Public health professionals and clinicians may need to consider the measurement of the suspected endocrine disruptors. Additionally, it may be beneficial to include the analysis of mixtures of endocrine disruptors; mixtures may play a role in the development of health issues instead of focusing on individual chemicals (Lee, 2018).

Research relating to endocrine disrupting chemicals and the COVID-19 pandemic may prove to be beneficial in future endeavors. Disorders, such as Type II diabetes, cardiovascular disease, and obesity have shown to be strongly linked to COVID-19 cases (Wu et al., 2020). Obesity promotes high basal inflammation which contributes to insulin resistance and eventual adipose tissue infiltration. Substances like BPA have been linked to the stimulation of pro-adipogenic signaling through PPARγ (Wu et al., 2020). Given the current situation of the global pandemic, it would be imperative that this phenomenon be explored to maximize the potential for discovering a possible trend.

Positive Social Change

Limiting the exposure of endocrine disrupting chemicals through the development of further regulations can present positive social change in reducing the prevalence of obesity. One major avenue to start this process is to provide a legal definition of endocrine disruptors that can be applicable to sectors of economy and jurisdictions of the world to a larger extent. The Endocrine Society, as mentioned in Kassotis et al. (2020) defined an endocrine disrupting chemical as “any chemical or mixture of chemicals that interferes with any aspect of hormone action.” If this definition is used or augmented for the better, in terms of providing additional detail in said definition, it could lead to additional public knowledge of obesogenic agents and to improved conscious health choices within individual, intrapersonal, organizational and community levels.

The last initiative for positive social change is to explore the option of changes in lifestyle. A possible alternative way to reduce the harm of endocrine disrupting chemicals is exercise, a feeding-fasting cycle, a high intake of dietary fiber, and a high intake of phytochemicals (compounds that are biologically active in plants; Lee, 2018). Healthy behaviors are known to increase the excretion of chemical substances in the body. Thus, improving eating habits within the United States and offering to have open discussions regarding what is put in food, and to a greater extent what is ingested or inhaled in the human body.

Conclusion

In summary, endocrine disrupting chemicals pose a threat to human health. The significant results relating to BPA, and to some extent AA/GA, show that endocrine disrupting chemicals have a relationship with obesity, while obesity is measured as BMI. Daily health risks associated with human BPA exposure presents and important challenge when trying to improve quality of life. Even with these statistically significant results, the true nature of endocrine disrupting chemicals is still surrounded with mystery. Endocrine disruptors have a nature of being inconsistent in various methodological concerns and present limitations (i.e. short lived endocrine disruptors, unpredictable net effects, and the near nonexistence of a nonexposure group).

Endocrine disrupting chemicals continue to be a prevalent issue within the United States and the field of public health with contributions to health disparities and disorders, like obesity. Additional studies and evaluations need to be conducted in order to report the relationship between endocrine disruptors. Lastly, proper clinical and practice protocols need to be made to ensure the exposure obesogenic chemicals can be proved in human models to match the evidence that has previously been provided. Regardless of the results, there is a growing need to analyze and understand all factors that could contribute to the high incidence of obesity.

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